



U.S. Department of Transportation
**National Highway Traffic Safety
Administration**



Safety in Numbers

A Literature Review



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16. Abstract In the context of pedestrian and bicyclist safety, the theory of Jacobsen's 2003 "Safety in Numbers" (SIN) posits an inverse relationship between the extent of walking and bicycling and the probability of motorist collisions with pedestrians and bicyclists. A literature review was conducted to summarize the state of research on SIN and identify potential implications of the work. The review chronologically describes research developing the SIN concept and subsequent work testing and expanding the theory. The literature review considers fields of study and areas of practice including engineering, planning and land use, sociology, psychology, education, public health, enforcement, human factors, and others. This breadth was especially important due to the broad target audience of this report who may apply the literature review results to their own future practice. These include State Highway Safety Offices, national organizations interested in the SIN topic, constituents from the Federal Highway Administration, planners, engineers, educators, advocacy groups, policymakers, State DOTs, metropolitan planning organizations, and roadway users — motorists, pedestrians, bicyclists — and law enforcement professionals.			
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Executive Summary

In the context of pedestrian and bicyclist safety, the theory of “Safety in Numbers” (SIN) posits an inverse relationship between the extent of walking and bicycling and the probability of motorist collisions with pedestrians and bicyclists (Jacobsen, 2003). In other words, this theory proposes that when the volumes of bicyclists and pedestrians increase, the increase of bicyclist- and pedestrian-related crashes occurs at a slower rate than that of the volume increase. The implication of this theory is that, at the individual level, the probability of bicyclists and pedestrians being involved in crashes decreases as the volume of bicyclists and pedestrians increase. Such a perspective can be used to encourage programs and policies that expand the amount of walking and bicycling. However, this theory has faced challenges in the research community, with some research indicating the opposite effect; increasing rates of walking and bicycling can increase the risk of crashes involving vulnerable road users (Ramsey & Richardson, 2017). The research team notes that there is evidence that public health can be improved through increased physical activity (Laird et al., 2018; Norwood et al., 2014; Pucher et al., 2010); however, that was not the focus of this investigation.

A literature review was conducted to provide a comprehensive summary of the state of the research regarding SIN and identify potential implications of the work. The literature review was designed to consider multidisciplinary fields of study and areas of practice, including engineering, planning and land use, sociology, psychology, education, public health, enforcement, human factors, and others. This breadth was especially important due to the broad target audience of this report who may apply the literature review results to their own future practice. These audiences include State Highway Safety Offices, national organizations interested in the SIN topic, constituents from the Federal Highway Administration (FHWA), planners, engineers, educators, advocacy groups, policymakers, State DOTs, metropolitan planning organizations (MPO), roadway users — motorists, pedestrians, bicyclists — and law enforcement professionals.

Search terms were constructed to identify the greatest number of relevant papers, although not all papers explicitly used the phrase “safety in numbers.” The search terms were used to discover and obtain relevant documents, which were then subject to initial and then more-critical reviews. As part of the literature review, 250 items were critically reviewed, including domestic and international sources relevant to understanding the SIN concept.

Jacobsen (2003) completed the foundational research into the SIN theory, coining the term “safety in numbers.” He found that as the number of people walking or bicycling increased, the risk of motor vehicle and pedestrian or bicyclist crashes decreased. Jacobsen calculated that at the population level, the number of motorists colliding with people walking or bicycling will increase at roughly the 0.4 power of the number of people walking or bicycling. To exemplify this calculation, Jacobson gave the example of a community that doubled the number of people



walking or biking. Using his calculation, this community would expect crashes to grow by 32%. Following the publication of his work, there began an acceleration of research using the SIN terminology.

As the theory rose in popularity, some researchers began to critically question it. These researchers identified several flaws regarding SIN-related research but concluded that there is some effect present that research could not fully explain. Recent research into the SIN theory typically looked to apply Jacobsen's method to different datasets, and/or looked to incorporate other explanatory variables to better understand the effect.

As a part of this literature review, a sample of studies was analyzed to understand the robustness of the statistical methods and data used. Much like the research critical to the SIN theory, this statistical review highlighted methodological issues in several SIN-related studies. A weakness of many SIN-related studies is the data commonly used by researchers. The two required data sources to conduct a SIN-related study are exposure and safety, and there have been limitations with both types throughout the literature. Count or volume data are rarely readily available, and collecting this data is often resource intensive. Issues with safety data stem from underreporting of injury data in crash datasets developed through police crash reports. Some researchers have been successful in introducing variables describing the built environment and behavioral characteristics, but these topics are a current gap in SIN research and are often covered only briefly, if at all, by current research.

While the SIN theory is often used to support programs and policies that encourage walking and biking, it is important to realize that crashes, injuries, and fatalities will continue to increase as more road users are entering the system; the theory states that this increase will be at a rate less than the rate of increase in road users. This also assumes that all other elements of the roadway environment remain stable: other factors may change such as engineering countermeasures or bicycle helmet laws. Changes to these factors may affect walking and biking and safety outcomes. From a public health perspective, the SIN research underscores the need to consider these other factors when moving forward with programs to increase bicyclist and pedestrian activity. Given that there are still increases in bicyclist and pedestrian injuries as volumes increase, practitioners and advocates should consider adopting a multi-prong approach. The approach should include additional education to inform and support new and vulnerable road users who might adopt bicycling or walking as a mode of transit as well as education for road users about applicable laws and practices.

This literature review also identified a sample of programs and initiatives at transportation and advocacy organizations that work to increase pedestrian and bicycle travel and safety. Many of these agencies have measures of success—whether that be implementing programs or initiatives, seeing increases in bicycle and pedestrian volumes, and/or decreasing bicyclist and pedestrian crash rates. However, program evaluation results are not formally published or do not make the correlation between an increase in pedestrian and bicycle volume and reduced crashes, or the



other factors that may influence SIN. Further, this review showed that the SIN theory is more commonly referred to and used in academia than in practice. More information on the underlying explanatory factors could be useful to help transportation practitioners integrate the SIN theory into their planning and policy.

Despite the wealth of research on this topic, the exact cause of the SIN effect is unknown. Some research points to behavioral changes, others question the involvement of related infrastructure. There also are data gaps and methodological challenges, specifically regarding infrastructure and non-motorized volume data and frequently a lack of consideration of human behavior such as driver and other road user distraction. As work is advanced in SIN, it will be important to convey considerations to researchers and practitioners seeking to use SIN to develop policies and initiatives.



Introduction

Fatalities involving bicyclists and pedestrians continue to rise. While total motor vehicle fatalities increased an estimated 19% over the last decade (2011-2020), bicyclist fatalities increased 31% and pedestrian fatalities increased 40% (National Center for Statistics and Analysis, 2020a, 2020b; NHTSA, 2021). As a result, many agencies are trying to understand what factors influence bicyclist and pedestrian crash risk and how to better improve non-motorized safety. One of the factors that may help explain bicyclist and pedestrian crash risk is the concept of Safety in Numbers (SIN).

The phrase “safety in numbers” is commonly understood to mean that a person has a better chance of avoiding negative consequences in a group than when alone. In the context of walking and bicycling, there are two primary perspectives regarding SIN. The first perspective posits that the higher the volume of bicyclists and pedestrians, the greater their safety. This theory is in agreement with an initial study from 2003 that found an inverse relationship between the extent of walking and bicycling and the probability of a motorist colliding with a pedestrian or bicyclist, suggesting that the SIN concept can be applied to pedestrian and bicyclist safety. Based on this finding, the study concluded that the presence of pedestrians and/or bicyclists likely alters motorist behavior, thus creating a safer environment for all road users. As a result, the author inferred that pedestrian and bicyclist safety can be enhanced by implementing programs and policies that expand the amount of walking and bicycling (Jacobsen, 2003).

After its publication, the SIN theory received criticism from other researchers who thought that the statistical relationship between exposure and safety neglected to explore underlying behavioral and environmental explanatory mechanisms. Contrary to the SIN concept, an alternative theory posits that higher volumes of bicyclists and pedestrians increases the chances of a crash. As recently as 2017, a study in Melbourne, Australia, did not observe a SIN effect despite growing bicycling rates (Ramsey & Richardson, 2017).

Other studies such as the report from Bhatia and Wier (2011) acknowledge the need to research other potential influential factors (e.g., behavioral, environmental) before the benefits of SIN can be considered reliable. Furthermore, altering and/or creating policies/programs based on the SIN concept is rash and could potentially be detrimental to safety.

This literature review explored these competing perspectives by investigating and summarizing available studies on the topic of SIN. With the emphasis on providing multimodal transportation options, and the adoption of Complete Streets and Vision Zero plans and policies, it is even more vital to understand the implications of SIN and how it could impact choices in policy, design, and other safety interventions. Although there is evidence that public health can be improved through increased physical activity (Laird et al., 2018; Norwood et al., 2014; Pucher et al., 2010), that was not the focus of this investigation. The goal of this report is to allow the



reader to develop a clearer understanding of evidence related to the SIN concept and the factors which should be considered when implementing and evaluating policies or programs that promote walking and bicycling.

Relevant Terminology

As the SIN concept has been considered by many different researchers with many different transportation backgrounds, there is some variability in the language they use. For clarity, this report has adopted standard terminology to maximize consistency in writing. Some of the terminology used throughout the report is as follows.

Road/Roadway user – any motorized or non-motorized user of a transportation facility that is typically defined as being within the public right-of-way, including pedestrians, bicyclists, and motor vehicle drivers.

Crash – a collision involving a roadway user (motor vehicle, bicyclist, pedestrian) that may or may not involve another roadway user. This collision could take place in the travel lane of a roadway or also in a facility adjacent to the roadway, such as a shoulder, sidewalk, or sidepath.

Risk – the probability of a crash, usually defined as the number of incidents (crashes) per unit of time, distance, or population. The lower the risk of a crash, the safer that roadway user is.

Level of comfort – the roadway user comfort level given certain conditions and factors. Some roadway users may feel very comfortable using a facility that may make another user uncomfortable. Certain factors could influence the level of comfort such as age, ability, and experience, among others.

Exposure – the measure of opportunities for crashes to occur, usually expressed as time, distance, or a population. Exposure allows for comparisons of crash rates by normalizing the number of incidents against opportunities for them to occur.

Report Structure

The Report has been organized as follows.



Literature Review Methodology

This section presents an overview of the literature discovery and review process. The scope of the investigation is defined, and information is presented to describe the search terms used, sources considered, and document screening method.



Literature Review Findings

This section describes the history of the SIN concept including early research, explicit adoption of the term, and competing perspectives regarding its existence and relevance. Research uniquely focusing on pedestrians or bicyclists is highlighted. Different data sources, analysis techniques, and methodological considerations also are discussed.





Implications and Considerations

This section builds on what was observed in the literature review findings to characterize the state of the research and summarize key issues to be considered by those with an interest in the SIN concept.



Programs and Initiatives

This section provides an introduction to the state of the practice, providing a sample of bicycle and pedestrian programs in different communities around the Nation. Their objectives and metrics for success are discussed in the context of the SIN concept.



Conclusions

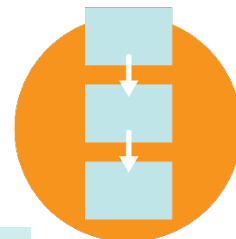
This section summarizes key observations during the literature review.

The icons shown above have been incorporated throughout the document to help readers identify content of interest.



Literature Review Methodology

This section presents an overview of the literature discovery and review process. The scope of the investigation is defined, and information is presented to describe the search terms used, sources considered, and document screening method.



Scope of the Investigation

The literature review was designed to consider multidisciplinary fields of study or areas of practice, as shown in Table 1. The wide scope of this literature review was selected for two reasons. First, the facets of the SIN concept span many fields and it is desirable to capture them all. Second, this report is intended for a broad target audience who may apply the literature review results to their future practice. These audiences include State Highway Safety Offices, national organizations interested in the SIN topic, constituents from the FHWA, planners, engineers, educators, advocacy groups, policymakers, State DOTs, MPOs, roadway users — motorists, pedestrians, bicyclists — and law enforcement professionals.

The literature review included domestic and international sources and focused on those sources from the past 15 years related to SIN. Older sources foundational to SIN were also included. Table 2 shows the number of sources collected by location (i.e., United States versus international). For the purpose of this literature review, studies labeled as international studies are those studies that used data or were conducted in one or more countries outside of the United States. International studies were included in the literature search as many methodologies and evaluation techniques related to the SIN concept are applicable to the present effort, despite differences in laws and culture when compared to domestic studies.

Table 1. Number of Sources by Field of Study or Area of Practice

Field of Study/Practice	# of Sources
Engineering	136
Planning/Land Use	58
Encouragement	54
Behavioral (Sociology)	52
Behavioral (Psychology)	52
Education	44
Public Health	24
Enforcement	23
Behavioral (Other)	12
Human Factors	10

Table 2. Number of Sources by Location

Location	# of Sources
International	141
United States	93
Both	15



Table 3 displays the number of sources by topic area, which are based on the research objectives identified in planning the review. An individual source may be categorized within one or more topic areas, and being categorized by the topic area indicates that the source discusses that topic (i.e., a source does not need to be focused on that topic to be categorized).

Information Sources and Search Terms

Search terms were carefully constructed and customized to address research objectives and maximize relevant search results to ensure an efficient search and review process. Table 4 displays the information sources and search terms used to collect relevant SIN research documents.

Most of the relevant research used the actual term “safety in numbers,” while some other sources used indirectly related terms (e.g., exposure, expectancy, volume). For example, the search results from the *American Journal of Public Health* did not include the exact term “safety in numbers” but instead referenced SIN using various other terms shown in Table 4. As a result, the search term “safety” was used instead of the term “safety in numbers” to expand the search results to include more of the indirect SIN research. Note that even sources that were not specifically focused on SIN often referenced SIN-related studies within, so the “safety in numbers” term was used even though it may not have been the primary research goal. In addition to the search terms identified in Table 4, sources were also identified and reviewed based on the research team’s knowledge on the topic and references within the collected literature.

Table 3. Number of Sources by Topic Area

Topic Area	# of Sources
Infrastructure	126
Findings That Support SIN	114
Includes/Discusses Collision Data	102
Factors Affecting Crash Rates	93
Programs/Efforts	67
Pedestrian/Bicyclist Behavior	31
Driver Behavior	30
Findings That Refute SIN	28
SIN Effects: Bicyclists Versus Pedestrians	8
Distraction	4

Table 4. Information Sources and Search Terms

Information Source	Search Terms
TRID	"safety in numbers" AND ("pedestrian*" OR "bicyclist*" OR "walker*")
Google Scholar	"safety in numbers" AND ("pedestrian*" OR "bicyclist*" OR "walker*" OR "road")
American Journal of Public Health	"safety" AND ("pedestrian*" OR "bicyclist*" OR "walker*") AND ("road*" OR "roadway*" OR "street*")
SWOV Institute for Road Safety Research	"safety in numbers" AND ("pedestrian*" OR "bicyclist*" OR "walker*")
ResearchGate	"safety in numbers" AND ("pedestrian*" OR "bicyclist*" OR "walker*")
Traffic Injury Prevention Journal	"safety in numbers" AND ("pedestrian*" OR "bicyclist*" OR "walker*")



Document Screening Method

All search results, except for a few sources that were obviously not relevant, were then recorded. Next, an initial review was conducted, which included providing an initial prioritization based on the abstract and a broader review of each source. Then, a critical document review was performed on sources classified as the highest priority levels and included more detailed documentation and annotation. Following the critical review of the literature, a sample of highly rated sources were reviewed to assess the robustness of the statistical methodology and results. Outcomes of the statistical review were integrated into the literature review findings.



Literature Review Findings

This section describes the history of the SIN concept (i.e., including research from before the SIN term was coined through recently published research) and competing perspectives regarding its existence and relevance. Research uniquely focusing on pedestrians or bicyclists is highlighted. Different data sources, analysis techniques, and methodological considerations also are discussed.

It should be noted in this review, the authors did not need to use the term “safety in numbers” to be considered. There are many studies of roadway user safety that are relevant to the SIN concept. However, not all authors explicitly use “safety in numbers” to define their work objectives or outcomes.

Much of the literature discussed in this report focuses on the analysis of safety data such as crash or injury records. Many of these studies employ statistical methods and models to draw conclusions from the data. One approach commonly used in this field of research is the use of generalized linear models (GLM). Whereas ordinary linear regression requires model residuals to follow a normal distribution, GLMs can be modified to use other distributions. GLMs are often named for their error structure (e.g., a “negative binomial GLM” refers to a GLM with residuals following a negative binomial distribution).

The Poisson and negative binomial distributions are generally used in the context of count variables (e.g., the number of crashes in a given time period or space) and are widely accepted methods for modeling vehicle crashes (Vogt & Bared, 1998). Because pedestrian- and bicyclist-related crashes are relatively rare depending on the study area and timeframe, there is often overdispersion in the data. Overdispersion occurs when there is more variability in the data than would be expected under the specified error distribution. Both Poisson and negative binomial modeling approaches provide similar results, but the latter is better suited to handle overdispersion. As such, researchers frequently use negative binomial GLMs when investigating SIN.



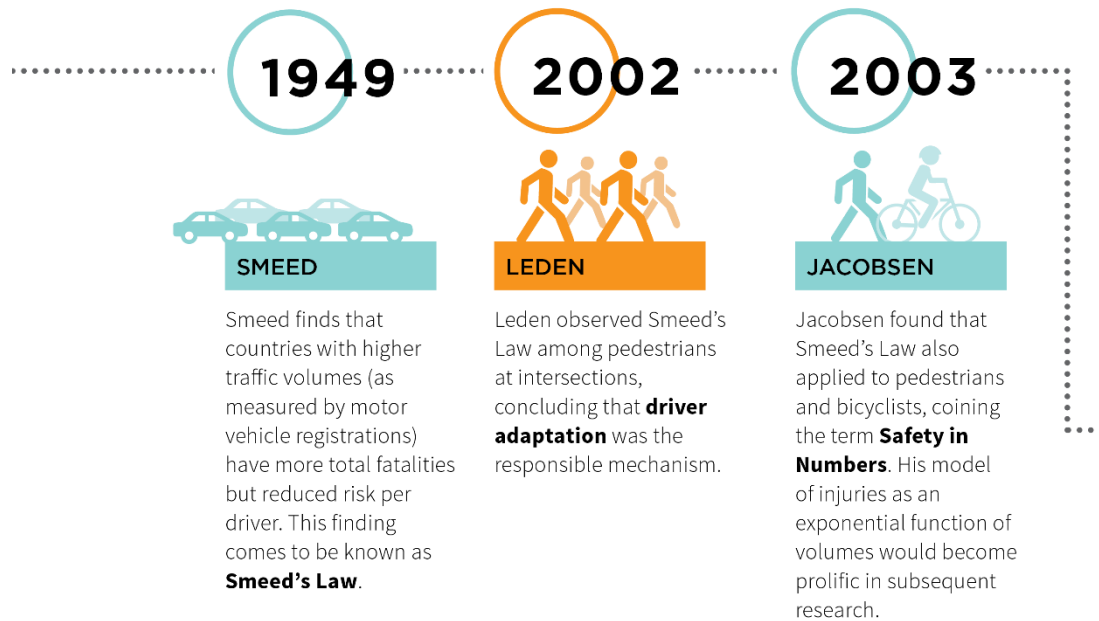
Ultimately, the choice of modeling technique is a decision made by the researcher based on a number of factors, with some project specific (e.g., data limitations), and some specific to the researcher (e.g., preference, familiarity with the models). More information, technical details, and guidance on selecting GLM model types can be found in a FHWA report titled *Accident Models for Two-Lane Rural Roads: Segment and Intersections* (Vogt & Bared, 1998).

Overview of the Literature Review Findings

The findings in this section are organized with respect to the development of the SIN concept, beginning with research in the 1990s and early 2000s that set the stage for SIN and culminating with more recent research that has both tested and expanded upon early SIN findings. Figure 1 depicts this chronology.



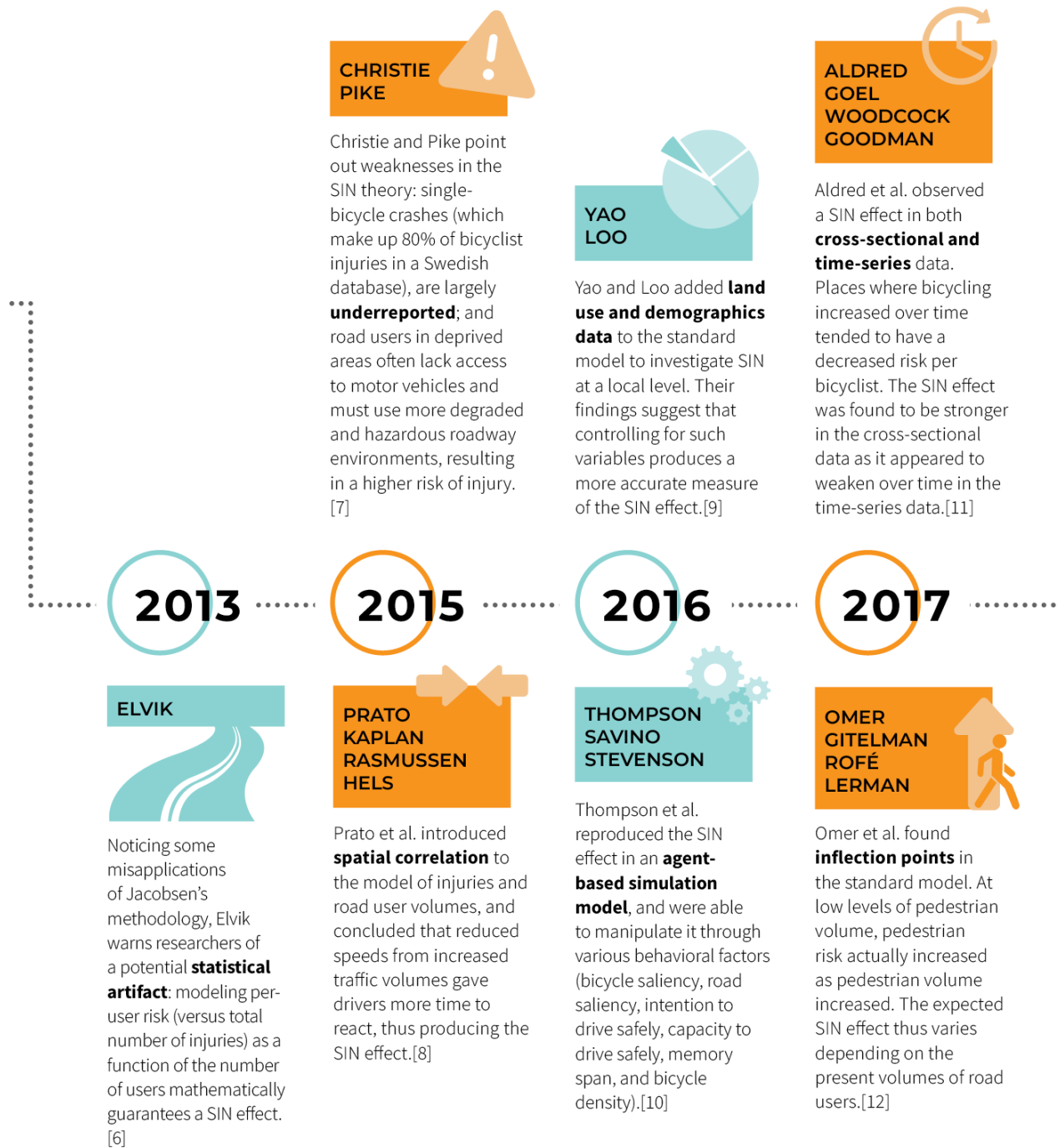
Figure 1. Timeline of SIN Research



Timeline of SIN Research



Figure 1 (continued). Timeline of SIN Research



Before “Safety in Numbers”

In the late 1990s and early 2000s several researchers were reviewing crashes at intersections and developing crash prediction models in order to understand the relationships between the different factors involved with roadway safety. Four examples that served as foundational research for the SIN theory were by Summersgill and Layfield (1996), Leden (2002), Lyon and Persaud (2002), and Raford and Ragland (2004).

Summersgill and Layfield (1996) studied crash risk based on 300 urban roads in England. As part of this effort, the team used negative binomial regression to develop crash prediction models for several scenarios (e.g., vehicle-only crashes, head-on crashes). Of relevance to SIN, the group developed models estimating pedestrian-related crashes. The two negative binomial regression models developed for pedestrian-related crashes were found to have exponents of 0.51 and 0.44 for the pedestrian flow variables, indicating a less-than-proportional increase in crashes given an increase in the number of pedestrians, hence reduced risk per pedestrian amid a larger number of pedestrians. This finding showed a non-linear relationship between pedestrian volume and crash rates and in the coming years would give support to the SIN theory.

Leden (2002) studied pedestrian crashes at intersections in Canada. As part of these studies, he analyzed 4 years of pedestrian and vehicle flow data from Hamilton, Ontario. He found that when considering pedestrian risk as the number of pedestrian-related crashes per pedestrian at the intersection, risk decreased as the pedestrian flow increased. Leden hypothesized that an explanation for this finding was increased driver awareness due to increased pedestrian flow.

In the same year, Lyon and Persaud (2002) also published a paper describing crash prediction models to estimate pedestrian-related crashes in Canada using data from crashes in Toronto, Ontario and Hamilton, Ontario. These researchers focused most of their paper on developing the crash prediction model and mentioned their finding of a non-linear relationship between exposure and risk only briefly. While brief, Lyon and Persaud’s findings reinforced those of Leden and other early work on SIN.

Raford and Ragland (2004) published a paper describing a technique to model pedestrian volumes. This model, known as Space Syntax, had been developed by the University College of London in the 1980s and had been used across Europe and Asia for planning projects. Even with such international use, the method was largely unknown previously to engineers and planners in the United States. To estimate pedestrian volumes, Raford and Ragland used Space Syntax to analyze layout and connectivity of Oakland, California, to generate potential pedestrian movements. These potential movements were compared with sampled pedestrian counts at key locations and land-use indicators such as population and employment density. Finally, pedestrian volumes were estimated at the street-level for the entire city.







While the term “safety in numbers” is not used by Raford and Ragland, key findings from this paper directly support the SIN theory. The researchers found that the resulting model for Oakland showed that high pedestrian exposures did not necessarily correlate with increased motor vehicle and pedestrian collisions. The resulting model found that many of the most dangerous intersections in Oakland actually received a lower number of absolute collisions, but also lower numbers of pedestrian volumes, and conversely that many of the intersections with high pedestrian volumes often had a lower risk of pedestrian-related crashes.

Summary

A summary of the literature discussed in this section is presented in Table 5. Aside from Raford and Ragland’s work, these examples studied crashes at intersections.

Table 5. Overview of Studies Covered in the Before “Safety in Numbers” Section

Year	Author	Methodology	Objective	Road Users Studied	Results
1996	Summersgill & Layfield	Generalized linear models (negative binomial)	Study crashes on urban road segments and at urban T-intersections.		Support SIN
2002	Leden	Generalized linear models (error structure not provided)	Pedestrian safety at semi-protected schemes, where left-turning vehicles face no opposing traffic but have potential conflicts with pedestrians, were compared with pedestrian safety at normal non-channelized signalized approaches, where right-turning vehicles have potential conflicts with pedestrians.		Support SIN
2002	Lyon & Persaud	Generalized linear models (negative binomial)	Crash prediction models are developed for three- and four-legged urban intersections, with and without signal control.		Support SIN
2004	Raford & Ragland	"Space Syntax" software	Develop citywide pedestrian volume estimates.		Support SIN

Coining “Safety in Numbers”

Prior to research into the SIN theory, Smeed (1949) completed groundbreaking research that later became known as Smeed’s Law. This law proposed that increases in traffic volumes led to a decrease in fatalities per vehicle (but not necessarily a decrease in the number of fatalities). With Smeed’s research serving as a basis of his hypothesis, Jacobsen (2003) questioned whether the relationship between the number of pedestrians or bicyclists and motor vehicle traffic volumes was linear. He studied five datasets representing several countries to compare the amount of walking or bicycling and the injuries resulting from collisions with motor vehicles. He found that as the number of people walking or bicycling increased, the relative risk of a motor vehicle and pedestrian or bicyclist crash decreased. Jacobsen calculated that at the population level, the





number of motorists colliding with people walking or bicycling will increase at roughly 0.4 power of the number of people walking or bicycling and coined the term “safety in numbers” to describe this effect. This means that if the number of people walking or bicycling doubled, the number of crashes between them and motor vehicles would increase by a factor of $2^{0.41} = 1.33$, or only 33%. Jacobsen questioned the cause of this effect and like Leden, hypothesized that the effect is driver adaptation in areas of increased pedestrians and bicyclists. While Jacobsen’s work was foundational to SIN research, there were limitations to this study. Jacobsen’s models were simplistic and did not consider metrics aside from exposure and safety nor consider motor vehicle volumes.

Robinson (2005) later completed another foundational and frequently cited study on SIN. Robinson looked to see if Jacobsen’s work was applicable in Australia by looking at the SIN effect in reverse. While bicycle ridership increased in Australia in the 1980s, it decreased in the 1990s at the same time a helmet law was enacted along with high-profile anti-speeding and anti-drunk driving campaigns. Using bicyclist counts and hospital data, Robinson found that when comparing data before and after the helmet law was enacted, deaths and serious head injuries decreased for both pedestrians and bicyclists. However, Robinson identified that the exposure measurements decreased at a higher rate than the safety measurements. This finding enabled Robinson to conclude that this difference in rates showed that risk and exposure do not have a linear relationship and supports the idea that there is a SIN effect in Australian data.

Summary

A summary of the literature discussed in this section is presented in Table 6. Both studies looked at pedestrian and bicyclist risk as exposure varied.

Table 6. Overview of Studies Covered in the Coining “Safety in Numbers” Section

Year	Author	Methodology	Objective	Road Users Studied	Results
2003	Jacobsen	Exponential regression	Examine the relationship between the number of people walking or bicycling and the frequency of crashes between motorists and walkers or bicyclists.		Support SIN
2005	Robinson	Simple temporal analysis and a simple before/after analysis	Study fatality and injury risks per bicyclist and pedestrian as exposure increases.		Support SIN

Subsequent Investigations of Safety in Numbers

It took some time before the term “safety in numbers” took hold in the research community. Jonsson (2005) completed one of the first studies to look at predictive models for pedestrian and bicyclist crashes after Jacobsen coined the “safety in numbers” term. In Jonsson’s doctoral



dissertation, he looked to improve predictive crash models with a specific focus on vulnerable road users. He used police reported crash data, exposure data, and field data to model crashes in six Swedish cities (n=393 road segments). While he never uses the term “safety in numbers”, the results of his generalized linear models show a non-linear relationship between the flow of vulnerable roads users and crashes, providing support for the theory.

As another example, Zegeer et al. (2005) conducted a study of 5 years’ worth of data at 2,000 U.S. crosswalks, half marked and half unmarked. The objective of this study was to compare the safety of the two crosswalk types and provide guidance to practitioners. As a part of this study, the researchers developed several crash prediction models. Of relevance to the SIN theory, two models developed to predict crashes showed a non-linear relationship between pedestrian volume and crashes, thus lending further support to the SIN effect. While this relationship is similar to that shown by Jacobsen (2003), the term “safety in numbers” is absent from the report and Jacobsen’s research is not cited by Zegeer et al.

Beginning in the late 1990s, Turner (2000) had been researching motor vehicle crashes and publishing papers that produced crash prediction models using generalized linear models, with early work focused on developing models for specific crash scenarios (e.g., rear-end crash at a traffic signal) based on motor vehicle flow (Turner, 2000). In 2005, Roozenburg and Turner published work on crash rates for pedestrians and bicyclists in New Zealand. This work appears to be one of the earliest cited examples of the use of SIN in the context of transportation research (Roozenburg & Turner, 2005). Turner et al. (2006) completed a study for the Land Transport of New Zealand, which resulted in several papers, including one on pedestrian- and bicyclist-related motor vehicle crashes. They developed dozens of crash models in different scenarios (e.g., sideswipe crash at a four-way intersection) using data from intersections and mid-block crossings in three cities in New Zealand. Turner et al. found that several of these models supported the SIN theory, showing that the increase in crashes is expected to be less than the increase in exposure.

Around the same time as Turner and Roozenburg’s work, SIN research inspired by Jacobsen’s work was under way in the United States and Australia. Geyer, Pham, et al. (2006) revisited the methodology from Raford and Ragland (2004) to specifically look at the relationship between pedestrian volume and pedestrian-related crashes. Citing Jacobsen’s work, they published a paper aptly named “Safety in Numbers: Data from Oakland, California” which used data from 247 intersections in Oakland, California, to model the effect of pedestrian volume on the number and rate (number of collisions per pedestrians) of pedestrian-related collisions at or near these intersections. Findings from this effort were consistent with Jacobsen’s findings; the estimate for the power coefficient for annual pedestrian volume was 0.61 meaning that a doubling of the number of pedestrians present would only increase the estimated number of pedestrian-related crashes by 53%.

Doubling the number of pedestrians would increase the number of pedestrian-related crashes by 53% (Geyer, Pham, et al., 2006).



Bonham et al. (2006) looked to replicate the previous work of Jacobsen and others in South Australia by examining the relationship between bicyclist volumes and bicyclist crashes at different scales (e.g., intersection, road segment, area). Bonham et al. did not develop and present statistical models in this paper; however, they developed scatter plots and drew an exponential line relating log(trips) to per-bicyclist crash risk. The results of this analysis support the SIN theory, showing inverse relationships between number of crashes and number of bicyclist trips.

Few research studies were published on the SIN theory between 2006 and 2009. Hardwood et al. (2008) continued the work of Zegeer et al. (2005) and published a National Highway Cooperative Research Program (NCHRP) web-only document on pedestrian safety. Like Zegeer et al.'s previous work, this publication does not use the term "safety in numbers" nor does it reference Jacobsen's research. However, it does follow a similar methodology and has similar results. Among other results, Hardwood et al. developed two models, one for a 3-legged signalized intersection and one for a 4-legged signalized intersection, based on data from 450 and 1,433 intersections, respectively. The exponent for pedestrian volume was found to be 0.41 for the 3-legged intersection and 0.45 for the 4-legged intersection indicating that the number of crashes would increase by the power of 0.41 and 0.45, respectively, of the increase in pedestrian volume. An example of this would be if the pedestrian volume doubled, then the crashes would increase by 33% for a 3-legged intersection and increase by 37% for a 4-legged intersection.

An uptick in the number of studies related to the SIN theory began in 2009. In many cases, these studies referenced one or more SIN papers (e.g., Jacobsen's work), but may or may not have

High proportions of bicycling commuters correlate with low casualty rates among cyclists (Vandenbulcke et al., 2009).

included the term "safety in numbers" within the body of the paper. Vandenbulcke et al. (2009) looked to understand how city size and land use affect bicycle safety in Belgium. Data were grouped by political boundaries (e.g., municipality) and studied. They found that urban areas have a higher percentage of bicycle use than more rural areas; however, the researchers also found that areas slightly less dense than urban areas ("regional towns") have the highest percentage of bicyclist use. When studying bicycle-related crashes in those regional towns, they found that high

proportions of bicycling commuters were correlated with low casualty rates among bicyclists, supporting the SIN theory.

Nordback and Marshall (2010) conducted a simple analysis of bicycle crashes, bicycle volume, and traffic volume. While this analysis was not robust enough to determine statistical significance, findings show that while bicycle-related crashes do appear to increase with motor-vehicle volumes, bicycle-related crashes may stay constant or even decrease with increasing bicycle volumes. Also, safety per bicyclist seems to increase with increasing bicycle use, especially for bicyclist volumes above 1,000 bicyclists per day.



Schneider et al. (2010) conducted research into pedestrian crash rates with an objective of creating crash prediction models. While this research did not explore the SIN concept explicitly, Schneider et al. found that modeling the natural logarithm of pedestrian and motor vehicle volumes produced more accurate crash predictions than the raw counts. This finding supports the SIN concept in that the relationship between pedestrian crossing volumes and crashes is not linear. In addition to supporting the SIN concept, this source identifies infrastructure and land use components that seem to affect pedestrian crash rates in intersections.

Belgian researchers Daniels et al. (2010) completed two studies during this time focusing on crashes at roundabouts. In their first study, they developed Poisson and gamma models based on data from 90 roundabouts in Belgium. The objective of these models was to estimate the several roundabout-related crash types, including: crashes with bicyclists, crashes with mopeds, and crashes with pedestrians. The resulting models all supported the theory of SIN for bicyclists and moped riders. For pedestrians, only the Poisson models supported the SIN theory.

In their follow-up study, Daniels et al. (2011) increased the sample size of roundabouts from 90 to 148 and made a distinction between single-vehicle and multi-vehicle crashes. The modeling techniques in the second study aligned closely with that of their previous. Results of this study agree with their previous work; namely, vulnerable road users are overrepresented in crashes then could be expected based on their presence in traffic and that modeling these crashes shows a SIN effect.

Turner et al. (2011) continued previous work (Turner et al., 2006) by collecting data in both New Zealand and Australia. The researchers analyzed 485 intersections and developed 19 crash prediction models representing 6 crash scenarios (e.g., midblock crashes, left-turn crashes at intersections). Turner et al. used generalized linear modeling (Poisson and negative binomial) to develop models representing the different scenarios. These models included various dependent variables, including road features and bicyclist volume, and all 18 of the significant models showed a non-linear relationship between crashes and bicyclist volume, supporting the SIN theory. The researchers were unable to develop a significant model for one scenario; this scenario described "other" crashes for intersection approaches that included bicycle facilities. The definition of "other" crashes was not provided in the paper; however, the authors did provide two examples of such crashes: crashes that were a result of increased bicyclist volume on footpaths and crashes between bicyclists and parked vehicles (e.g., the driver opening their door - dooring).

Most of this previous work, during the early 2000s, was related to crash and geometric design analysis. The implications on agency or program planning and policy was not yet explored and few publications had been identified where transportation agencies were referencing or using the SIN theory for planning or policy purposes. In 2005 the European Transport Safety Council (2005) developed a report on transportation safety and sustainability. This report focused on many modes of transportation but did introduce the concept of SIN. When discussing bicyclists,



the authors referenced past studies on SIN and data from European countries to show how increases in bicycling volumes improve safety and justify bicycling as a public health benefit. In an American example, Dossett et al. (2008) developed and presented a business case for the City of Minneapolis, Minnesota to develop a bike share program. As part of this document, the authors discuss the SIN effect. Similar to the European Transport Safety Council report, the authors do not seem to incorporate the SIN effect into any calculations but cite the effect to justify the benefit of increasing ridership in the city.

Summary

A summary of the literature discussed in this section is presented in Table 7. A common theme from these studies was that many of them developed crash prediction models, and these models showed a non-linear relationship between exposure and crash rates supporting the SIN effect.

Table 7. Overview of Studies Covered in the Subsequent Investigations of Safety in Numbers Section















Year	Author	Methodology	Objective	Road Users Studied	Results
2005	European Transport Safety Council	Literature review	Study existing research to identify approaches to address problems in transport safety policy.		Neither Support nor Refute SIN
2005	Jonsson	Generalized linear models (quasi-Poisson)	Develop crash prediction models for urban road segments.		Support SIN
2005	Roozenburg & Turner	Generalized linear models (Poisson and negative binomial)	Develop crash prediction models for signalized intersections.		Support SIN
2005	Zegeer et al.	Generalized linear models (Poisson and negative binomial)	Determine whether marked crosswalks at uncontrolled locations are safer than unmarked crosswalks under various traffic and roadway conditions and provided recommendations on how to provide safer crossings for pedestrians.		Support SIN
2006	Bonham et al.	Simple analysis	Study the risks that bicyclists face and the extent to which levels of bicycling impact upon bicyclist safety.		Support SIN
2006	Geyer, Pham, et al.	Space Syntax software, generalized linear models (Poisson)	Model the effect of pedestrian volume on the number and rate of vehicle-pedestrian collisions at or near intersections.		Support SIN
2006	Turner et al.	Generalized linear models (negative binomial)	Develop crash prediction models for signalized intersections, roundabouts, and mid-block locations.		Support SIN



Table 7 (cont.). Overview of Studies Covered in the Subsequent Investigations of Safety in Numbers Section

Year	Author	Methodology	Objective	Road Users Studied	Results
2008	Harwood et al.	Generalized linear models (negative binomial)	Develop pedestrian safety prediction models for use in the Highway Safety Manual.		Support SIN
2009	Vandenbulcke et al.	Cluster analysis	Study the spatial patterns of bicycle use for commuting and the risk bicyclists run being injured in a crash when commuting to work in Belgium.		Support SIN
2010	Daniels et al.	Generalized linear models (Poisson and gamma)	Explore the safety performance of roundabouts.		Support SIN
2010	Nordback & Marshall	Simple analysis	Examine the correlation between the number of bicyclists on a roadway and the number of crashes involving bicyclists.		Support SIN
2010	Schneider et al.	Generalized linear models (negative binomial)	Analyze pedestrian crash risk along arterial and collector roadways.		Support SIN
2011	Daniels et al.	Generalized linear models (Poisson and gamma)	Refine crash prediction models for roundabouts.		Support SIN
2011	Turner et al.	Generalized linear models (negative binomial and Poisson)	Study bicyclist crash risk on urban road segments, signalized intersections, and roundabouts.		Support SIN

Questioning the Validity and the Application of Safety in Numbers

With this increased focus on the SIN theory, researchers began to critically review and even challenge the idea. One of the first examples was a literature review published in 2009, where Elvik (2009) studied the non-linear relationship between exposure and risk to understand how a SIN effect could exist when vulnerable road users have a much higher risk of injury or death compared to motor vehicle drivers. His literature review concluded that there is a non-linear relationship; however, he found that the SIN effect was only demonstrated when there was a large transfer of motorized trips to a non-motorized mode. He did note several concerns with the SIN effect, specifically:

- Crashes involving vulnerable road users are poorly reported in official statistics.
- The exact shape of the non-linear relationship for risk is unknown. It is possible that the SIN effect strengthens, weakens, or ceases to exist as a function of the number of vulnerable road users present.



- Data regarding injuries between vulnerable roads users (e.g., crash involving a bicyclist and pedestrian) are largely nonexistent, so it is unclear how increasing the volume of vulnerable road users will affect safety amongst themselves.
- The percentage of motorized trips transferred to a non-motorized mode required to make a SIN effect present may be unrealistic in many situations.

Elvik (2013) reviewed common crash prediction models to better understand if these models can completely confirm the existence of a SIN effect. In this paper, Elvik critically reviewed the model used in Jacobsen's research (Jacobsen, 2003) that predicted the relative risk for a unit of walking or bicycling. This equation is:

$$\frac{I}{E} = aE^{(b-1)} \quad (1)$$

Where:

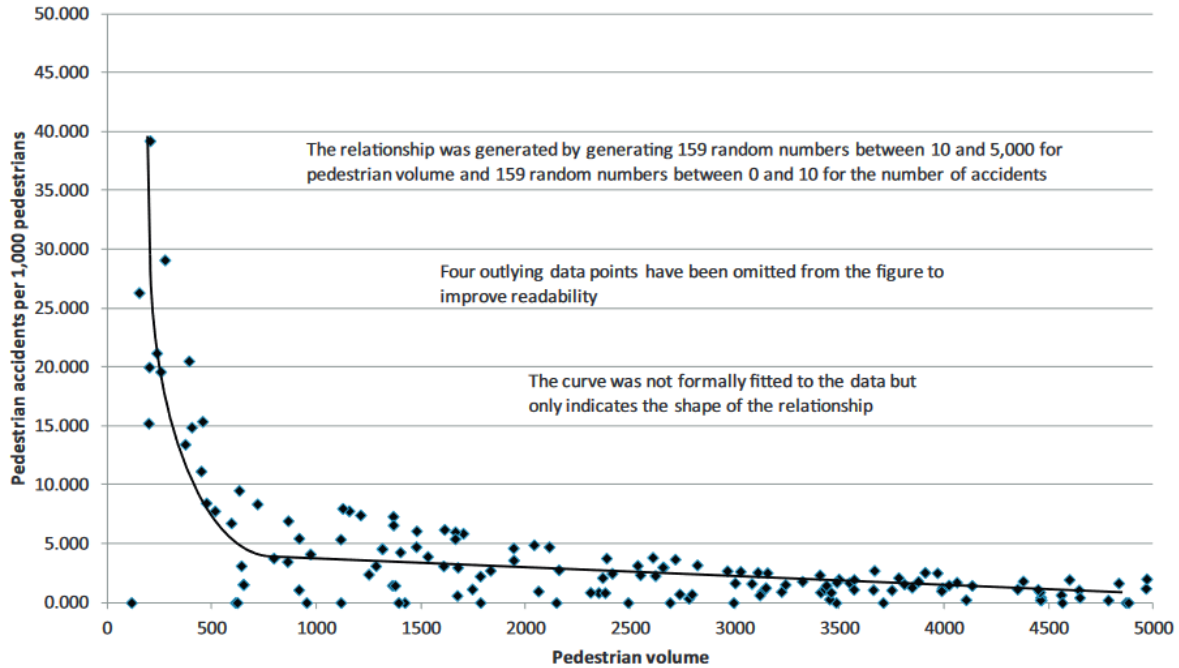
- I is the measure of injuries,
- E is the measure of walking or bicycling, and
- a and b are computed parameters using least squares analysis.

Elvik showed that there are inherent flaws with trying to provide a SIN effect using this model due to the relationship between the model's variables. He focused on the variables for risk and exposure. In some cases, risk can be measured as number of crashes or injuries per kilometer walked or biked. Exposure can also be measured by number of kilometers walked or biked per resident.

If risk and exposure are both measured in this fashion, there is an inherent relationship between the two – distance traveled. Elvik demonstrated this relationship using random numbers for motor vehicle volumes, pedestrian volumes, and number of crashes with realistic upper and lower limits based on a dataset from Oslo, Norway (Figure 2). In his later work in 2015, Elvik (2017) performed a meta-analysis on studies related to SIN and found that 8 of the 26 studies selected for inclusion in the meta-analysis had to be removed due to the fact they used this flawed model form.



Figure 2. Example of a SIN Effect Generated With Random Numbers (Elvik, 2013)¹



The other crash prediction model that Elvik discussed is as follows:

$$\text{Expected number of crashes} = e^{\beta_0} (VRU)^{\beta_1} (MV)^{\beta_2} e^{(\sum_{i=1}^n \beta_i X_i)} \quad (2)$$

Where:

- *VRU* is the vulnerable road user (e.g., bicyclist, pedestrian) volume,
- *MV* is the motor vehicle volume,
- *e* is the exponential function,
- *X_i* are risk factors (e.g., traffic speed); and
- *β_i* are coefficients typically estimated by regression analysis.

Elvik showed that this model is more appropriate for researching SIN, as it uses actual exposure data (e.g., counts) rather than proxy values and shared components. This model also allows some ability to control for confounding variables. Even while this model form is superior for investigating the SIN effect, Elvik shows how if the sum of the exponents for the motor vehicle and vulnerable road users variables (β_1 and β_2 in the equation above) is greater than one, there is not a complete SIN effect, but rather a partial effect that is only observed when the motor vehicle volume is held constant.

Recall that SIN does not predict a decrease in total crashes, but rather a smaller increase in crashes than a corresponding increase in road users. The exponents in the above model describe the relationships between the number of crashes and the number of different road users. Elvik reports mean values of exponents for pedestrians and vehicles of 0.58 and 0.53, respectively.

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The multiplicative increase in the expected number of crashes due to a doubling of pedestrian volume is therefore equal to $e^{\beta_{PED} \ln(2)} = e^{0.58 \ln(2)} = 1.49$. In other words, a 100% increase in pedestrian volume is associated with a 49% increase in crashes. Similarly, the effect of doubling motor vehicle volume on the number of crashes is equal to $e^{\beta_M \ln(2)} = e^{0.53 \ln(2)} = 1.44$ (a 44% increase in crashes with a 100% increase in motor vehicle volume).

These mathematical relationships rely on the principle of *ceteris paribus*, or “all else equal.” The concurrent 100% increase in pedestrian volume and 49% increase in crashes assumes that motor vehicle volume went unchanged. In the real world, both volumes would change simultaneously. If they both doubled, then crashes would be expected to increase by a factor of $1.49 \times 1.44 = 2.16$. In other words, doubling the volume of both groups results in a more-than-doubling of the total number of crashes. This result, the percent change increase in crashes greater than the percent change increase in number of road users, will always occur when the sum of the exponents is greater than 1.

Elvik went on to show the exponent for traffic volumes for nine studies on SIN using this model and highlighted that 13 of the 19 models developed in these studies have a sum of the exponents greater than 1, indicating that most of these models are only showing a partial SIN effect. The implication of this finding is that for most of the models Elvik studied, the SIN effect would be present if pedestrian or bicyclist volumes increased only when motor vehicle volumes stayed constant or decreased.

In addition to Elvik’s work, Bhatia and Wier (2011) also critically reviewed the SIN effect. The main argument in this paper was that, at least at the time of writing, the SIN effect was not well understood but was becoming more commonly referred to when developing transportation policy. Bhatia and Wier argued that without clearly understanding the mechanisms behind this effect, making policy decisions could result in unintended consequences. For example, the authors pointed out the higher risk per mile of travel for bicyclists and pedestrians and that this risk is not uniform across age groups (e.g., younger people are more likely to be injured and older people are more likely to be killed). Bhatia and Wier discussed several common analysis methods used in studies on the SIN effect and determined that the methods seemed sound; however, the studies and findings were insufficient to make a valid causal inference regarding the direct effect of pedestrian numbers on safety. The authors contended that by focusing on the reduction of risk to the individual, the SIN effect hides the additional burden of injuries and fatalities to the system and that good planning and policy should aim to decrease the total number of injuries and fatalities, not simply the risk to the individual user. They suggested that to use the SIN effect properly, more research is needed to understand how other variables, such as land use and infrastructure, play a role in the effect. Only with this understanding will planners and practitioners be able to carefully apply the SIN effect to planning and policy.

In the same year, Moudon et al. (2011) studied the risk of pedestrian injury and fatality in collisions with motor vehicles using data from King County, Washington, and tested the SIN

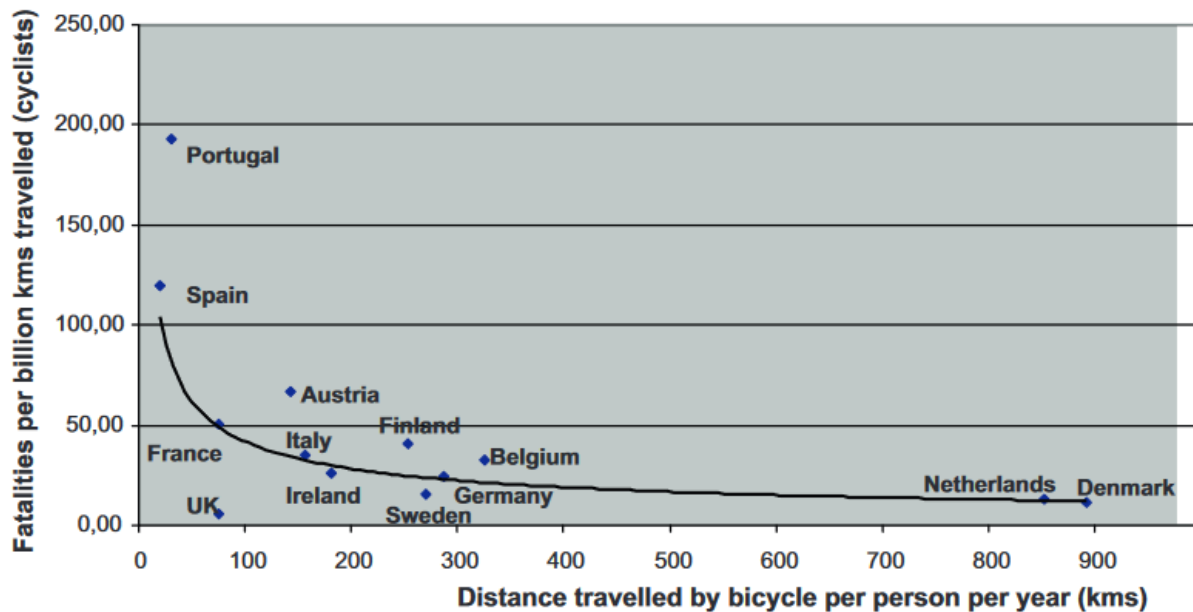


theory with regard to pedestrians. For this study, the researchers collected 5 years of pedestrian collision data, traffic exposure data (e.g., vehicle volumes, transit ridership), and land use information. It should be noted that pedestrian exposure (e.g., manual counts) data were not collected as a part of this study, nor was pedestrian activity estimated or modeled. Instead, proxy values, such as neighborhood density, were used. In addition, this study looked to compare risks of serious and fatal crashes to crashes resulting in minor injuries. In other words, crashes resulting in minor injuries served as the baseline to compare against. The researchers modeled the data using a binary logistic regression (unordered model). Findings showed that the likelihood of severe injury or death was positively related to residential density. While residential density is not equivalent to bicyclist and pedestrian exposure, it can be considered a proxy measure for those activities.

In the following year, Wegman et al. (2012) pointed out the dangers of bicycling when compared to driving a motor vehicle and highlighted that in many cases the transportation network is designed with motor vehicles in mind, so simply adding bicyclists to the network will not necessarily improve safety. Wegman et al. acknowledged that countries such as the Netherlands and Denmark have very high levels of bicycle use and lower bicyclist risks than countries with lower bicycle use. However, they also pointed out that there is a great variance in observed risk for countries with low bicyclist use (Figure 3), and this variance points to factors in addition to (or aside from) exposure affecting bicyclist risk. Another point made by Wegman et al. is the absence of single-bicycle crashes in many SIN studies. These crashes make up a significant number of bicyclist injuries and are often underreported. Further, many of the SIN studies focus on only police reported crashes, which often do not include any single-bicycle crashes. These researchers believed that before attracting new bicyclists, planners should develop well-designed bicycle facilities to reduce risks for bicyclists.



Figure 3. Relationship Between Bicyclist Use Rates and Fatalities for European Countries (Wegman et al., 2012)²



Macmillan (2012) also questioned the SIN concept by studying how commuting affects public health in New Zealand. To accomplish this task, Macmillan developed a simulation model that, among other things, estimated bicyclist injuries. When developing this model, Macmillan attempted to introduce a factor for the SIN effect. To do so, Macmillan tested two different models, one with a constant injury rate and one with an injury rate modeled as the function as described by Jacobsen (2003). When comparing the result for models with and without the SIN factor, Macmillan found that adding the SIN factor worsened the model's fit.

One particular study in 2013 reported interesting results related to the validity of SIN regarding bicyclists. Wei and Lovegrove (2013) developed bicyclist crash prediction models for the

An increase in bicycle-related crashes is associated with increases in transportation infrastructure (Wei & Lovegrove, 2013).

Regional District of Central Okanagan, a mostly rural area consisting of Kelowna, British Columbia, and its surrounding area. Data used for these models consisted of socio-demographic information, transportation demand information, and road network information. Negative binomial regression was conducted to develop the models. This study did not look at the SIN effect directly. Instead, the researchers hypothesized that there is an inflection point in the curve representing the function of bicycle-related collisions and bicyclist exposure. Wei and Lovegrove further hypothesized that North America is currently on the

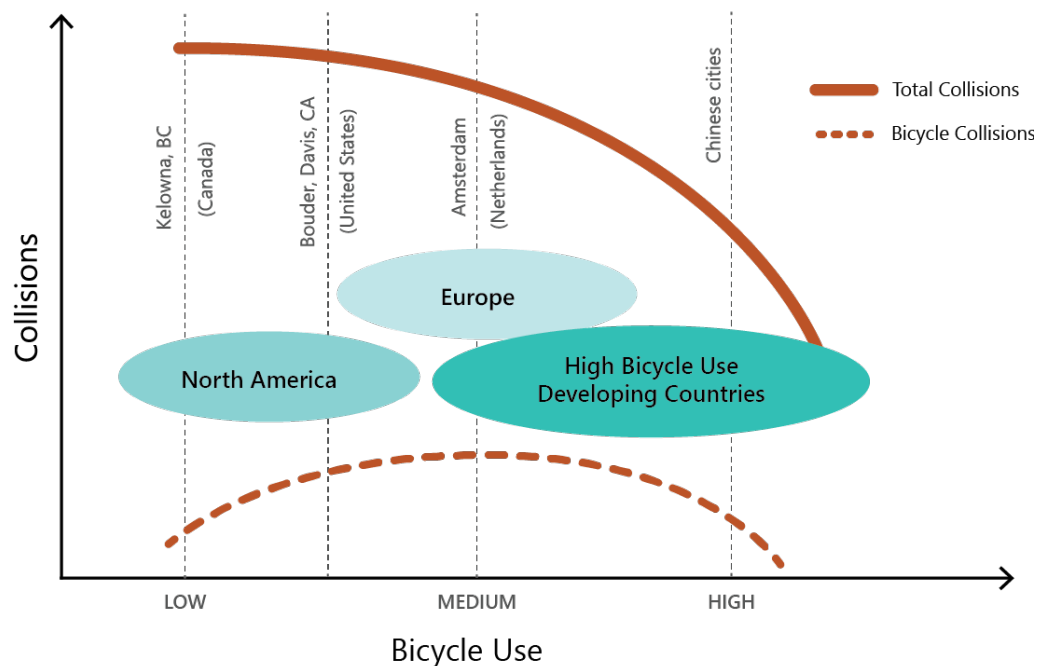
² Copyright 2012 by Elsevier. Reprinted with permission. Note that the decimal separator in this figure is a comma as is common in Europe.



starting end of this curve, and, therefore, will experience a growth in bicycle-related collisions more quickly than the growth in bicyclist exposure until the inflection point is reached (Figure 4). If correct, this finding would mean that the SIN effect would only be realized after some critical level of bicycle use. Before that level of bicycle use is obtained, the increase in bicycle-related crashes would outpace the increase in bicycle use.

Model results found that an increase in bicycle-related crashes is associated with increases in transportation infrastructure (e.g., total lane miles, bicycle lane miles, bus stops, traffic signals, intersection density) and that a decrease in bicycle-related crashes was associated with an increase in the number of people commuting by motor vehicle and the percentage of motor vehicle commuters. Wei and Lovegrove stated that these findings show support that rural areas in North America may be on the lower end of a bicycle exposure and collisions curve.

Figure 4. Hypothetical Function of Bicycle Use and Bicycle-Related Collisions (adapted from Wei & Lovegrove, 2013)³



The validity of the SIN theory regarding bicyclists was further studied by Thompson et al. (2014). The researchers used agent-based modeling to examine the SIN effect. These researchers developed a simulation that varied the percentage of bicyclists from 9% to 35% while leaving other variables constant. This experiment was repeated for varying levels of bicyclist density. The researchers were able to demonstrate a SIN effect similar to the effect reported in observational

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studies; however, this effect was only present in simulation scenarios with high bicyclist density. For scenarios with low bicyclist density, the relationship between bicycle exposure and bicyclist crashes was nearly linear, a finding one would expect if the SIN effect was not present. While these findings partly support the existence of a SIN effect, the findings show that the effect may not be dependent on the number of bicyclists but rather the density of bicyclists (i.e., the number of bicyclists within a certain area).

A study commissioned by the California Department of Transportation analyzed household travel survey data and estimated non-motorized traffic travel volumes and behaviors (Handy, 2014). As part of this study, the researchers analyzed crash patterns using only severe crashes and found mixed results with regard to SIN. The researchers used both national and State-level household travel survey data and classified the neighborhoods into four types (rural, suburb, urban, central city) based on characteristics of the built environment (e.g., population density, road density, local job access). In both the national and State-level cases, the researchers found that pedestrians were safest in the densest neighborhood types (central city). However, the national data showed that bicyclists were at most risk in the central city neighborhood types, and safest in rural and suburban neighborhood types. These bicyclist results directly refute the theory of SIN. When the researchers used the State-level household travel survey data, they found that bicyclists were almost equally as safe in central city and rural neighborhood types, and safest in the urban and suburban neighborhood types. The researchers explained this difference by noting that the State-level travel survey had higher central city volumes, and thus lower crash rates, than that of the national level. It should also be noted that the results could have been affected by the methodology by only including severe crashes and by not taking infrastructure availability into account.

An influx of in-depth research occurred in 2015 to assess the SIN concept by determining whether other variables could be contributing to the effect and defining important considerations for the effect. For example, Christie and Pike (2015) highlighted the underreporting of crashes involving non-motorized transportation. Citing data from the Swedish Traffic Accident Data Acquisition (STRADA) database, the researchers stated that 80% of bicyclist injuries stemmed from single-bicycle crashes (i.e., the bicyclist was the only involved party). The question of “who is safer?” was also discussed; the population of vulnerable road users does not necessarily mimic the population of the region they are traveling in, and some road users are more susceptible to injuries (e.g., younger and older populations) than others. Christie and Pike also discussed the applicability of the SIN effect to deprived areas where the number of vulnerable road users is often related to the lack of access to a motor vehicle. These deprived areas often have more degraded and hazardous roadway environments and, as such, may have a higher risk of injury to the users.

Additionally, Chen and Shen (2015) studied 10 years of data from Seattle, Washington, to understand the relationship between land use, the built environment, and bicyclist injury severity. Crash, land use, socio-economic, traffic, and exposure data were compiled and used.



Two modeling approaches were used: a multinomial logit model and a generalized additive model. Neither model found that the bicycle mode share variable had a statistically significant relationship with injury severity. As such, the authors were unable to demonstrate the existence of a SIN effect when focusing on injury severity.

Kröyer (2015) conducted an in-depth investigation into safety issues between motor vehicles and vulnerable road users. Using data from 113 intersections in Sweden, he studied the relationship between exposure and crash rates as well as speed and crash severity. While findings from his work largely agree with other similar studies and support the SIN effect, his work did include findings and discussions critical on the effect. First, Kröyer found a SIN effect to be present in single-pedestrian incidents, or instances where pedestrians were injured without the influence of others (e.g., tripped and fell). A common explanation for the SIN effect is that there is a behavioral change for drivers in areas with high concentrations of pedestrians or bicyclists, and this behavioral change is the reason for the effect. This explanation does not readily extend to single-pedestrian incidents. Kröyer hypothesized that this effect may be more likely due to infrastructure or other factors, and if that is the case, then the number of users may not be as important a factor in the effect.

To thoroughly evaluate the research conducted thus far, Elvik and Bjørnskau (2017) conducted a systematic review and meta-analysis on the SIN effect to investigate the body of literature as a whole and look to determine if a SIN effect exists. The researchers compiled a list of 26 studies researching the relationship between pedestrian and bicyclist safety and volume to use as the basis of the meta-analysis. The researchers further culled this list of studies to 15 as the remaining 11 had methodological shortcomings or were lacking details that prevented them from being included in the meta-analysis. In the end, a formal meta-analysis was conducted for 25 regression coefficients for motor vehicle volume (i.e., the exponent for the motor vehicle volume variable, shown as β_2 in equation (2), 15 regression coefficients for pedestrian volume, and 11 regression coefficients for bicycle volume. The potential for publication bias was studied using a trim-and-fill analysis (Duval & Tweedie, 2000). Results from this meta-analysis found no evidence of publication bias and indicated the existence of a clear SIN effect. The best estimates of the regression coefficients are 0.50 for motor vehicle volume, 0.43 for bicycle volume and 0.51 for pedestrian volume. Using the coefficient for pedestrian volume as an example, these findings suggest that if the number of people walking doubled, the number of crashes between pedestrians and motor vehicles would increase by a factor of $2^{0.51} = 1.42$, or 42%.

While results of this meta-analysis support the existence of a SIN effect, Elvik (2017) discusses several challenges with understanding and applying the effect. One potential issue is the crash prediction model used most commonly in SIN analysis: the negative binomial regression. Elvik states that this model does not allow for turning points in the model. For example, it is possible that without anything else changed, there could be negative safety implications if the percentage of vulnerable road users became too great, but these models have no way to depict this turning point given their format. Elvik's research found that no study in his review controlled



sufficiently for human behavior and for quality of infrastructure. Echoing other researcher concerns [e.g., Christie and Pike (2015)], he also pointed out that most of the studies were conducted using vulnerable road user crash data from official datasets and that these datasets greatly underrepresent minor crashes. Finally, Elvik's research included papers published prior to 2016, and given the state of research at this time, he concluded that it is still not possible to determine if the SIN effect is a causal relationship or merely a statistical relationship.

Building on the results of the systematic review, Elvik developed another paper (2017) to explore the strength of the SIN effect. In this paper, Elvik uses his past experience on the topic to categorize the main factors that, theoretically, could affect the strength of a SIN effect: (a) the number of pedestrians and/or bicyclists, (b) the number of motor vehicles, (c) characteristics of the pedestrians and/or bicyclists, and (d) characteristics of the traffic environment, such as infrastructure availability and design. Interestingly, characteristics of the motor vehicle driver were not mentioned.

Elvik (2017) stated that of the studies reviewed in the meta-analysis, no study included data on the characteristics of the pedestrians and/or bicyclists, and only a few included data on the characteristics of the traffic environment. As such, Elvik further studied factors related to the number of pedestrians, bicyclists, and motor vehicles. Much like his previous meta-analysis, this study was a cross-sectional study that looked at results of other existing studies.

Elvik's research developed two important findings. First, while the research did not include any longitudinal studies on SIN, the research did find that cross-sectional data show a tendency for the SIN effect to weaken as the number of pedestrians or bicyclists increases. Second, although this finding was not statistically significant, Elvik highlighted this weakening trend in the data and hypothesized that it may be due to the ratio of motor vehicles to bicyclists or pedestrians. Ultimately, he was unable to find a clear relationship between the strength of the effect and the ratio of the groups.

Summary

A summary of the literature discussed in this section is presented in Table 8. Studies in this section varied in terms of methodology and findings. In general, these studies suggest that the SIN theory needed more research to understand its cause and effect.



Table 8. Overview of Studies Covered in the Questioning the Validity and Application of Safety in Numbers Section















Year	Author	Methodology	Objective	Road Users Studied	Results
2009	Elvik	Literature review	Study existing research to understand the relationship between risks of injury to pedestrians and bicyclists and their exposure.		Identify Concerns with SIN
2011	Bhatia & Wier	Literature review	Critically examine the research foundational to SIN.		Identify Concerns with SIN
2011	Moudon et al.	Logistic regression (binary and ordinal)	Examine injury severity of pedestrian-motor-vehicle crashes based on characteristics of individual pedestrians and drivers and their actions, the road environment, and the built environment.		Refute SIN
2012	Macmillan	Participatory system dynamics modeling	Develop a conceptual model describing work commutes and public health that synthesizes knowledge from epidemiology, communities and policy makers.		Refute SIN
2012	Wegman et al.	Literature review	Discuss road safety problems of bicycling and bicyclists.		Identify Concerns with SIN
2013	Elvik	Generalized linear models (negative binomial)	Explore if a SIN effect and a hazard-in-numbers effect can co-exist in the same data.		Identify Concerns with SIN
2013	Wei & Lovegrove	Generalized linear models (negative binomial)	Develop crash prediction models for bicycle-related crash at an area-wide level (e.g., city).		Identify Concerns with SIN
2014	Handy	Cluster analysis	Study non-motorized travel in California and the factors that influence that travel.		Refute SIN
2014	Thompson et al.	Agent-based model	Replicate the SIN effect within a simple, simulated environment and vary bicycle density within the environment to better understand the circumstances under which SIN applies.		Identify Concerns with SIN
2015	Chen & Shen	Logistic regression (multinomial) and generalized linear models (generalized additive model)	Estimate the effects of land use, roadway design, and traffic control measures on bicyclist injury severity.		Refute SIN
2015	Christie & Pike	Literature review	Study SIN-related research.		Identify Concerns with SIN



Table 8 (cont.). Overview of Studies Covered in the Questioning the Validity and Application of Safety in Numbers Section

Year	Author	Methodology	Objective	Road Users Studied	Results
2015	Kröyer	Generalized linear models (negative binomial)	Explore the relation between exposure and the risk of a crash between pedestrians and motorized vehicles and between bicyclists and motorized vehicles occurring at urban intersections and how the speed environment and the victim's age relate to the injury severity/outcome once a pedestrian or a bicyclist has been struck by a motorized vehicle.		Identify Concerns with SIN
2017	Elvik & Bjørnskau	Systematic review and meta-analysis	Study the relationship between the number of crashes involving motor vehicles and bicyclists or pedestrians and the volume of motor vehicles, bicyclists, and pedestrians.		Support SIN
2017	Elvik	Literature review	Study the strengths of the SIN effect based on levels of pedestrian and bicyclist exposure.		Identify Concerns with SIN

Enthusiasm and Continued Research of Safety in Numbers

In parallel to the research questioning the validity and applicability of the SIN concept, new studies were being published with findings that supported the concept and encourage further research. Most of this research focused on conducting statistical analysis of safety (e.g., crash) and exposure (e.g., volume) data for pedestrians and/or bicyclists. These techniques are discussed below.

Trend Analysis

One of the early examples of this research was by Tin et al. (2011), who studied bicycling injuries and fatalities in New Zealand to understand if there was a correlation between the time spent bicycling and bicycling injuries. Data used in this study were based on national injury and fatality data as well as national household travel surveys. While Tin et al. did not use the term “safety in numbers,” the researchers found what they called a “risk in scarcity” effect where the risk profiles of bicyclists’ worsens when fewer people use a bicycle and more use a car. Specifically, Tin et al. found that there was a significant inverse association between the injury rate and the ratio of time spent bicycling to time spent traveling in a car. This finding also highlights the fact that the safety benefits of increasing bicycling could be dampened by increasing car use.

A 2012 report from the San Francisco Municipal Transportation Agency (2012) reviewed trends in bicycle use for the city between 2006 and 2011 and found a larger increase in percentage of bicyclist crashes than bicycle use, refuting the SIN effect. However, publications from the San Francisco Municipal Transportation Agency (2012, 2017) show that if the timeframe is increased



to include data up to 2015, then the increase in bicycling is much greater than the increase in bicycle-related crashes, providing support that a SIN effect is present in San Francisco.

While not part of a scientific study, the New York City Department of Transportation (NYCDOT) (2013) published a report on the state of bicycling in New York City. In this report the NYCDOT reported that the rate of crashes per bicyclist and per mile pedaled had fallen dramatically between 2000 and 2012, representing a 73% decline in the average risk of serious bicycling injury, while bicycling increased by 388% during this time frame.

NYCDOT reported the average risk of serious bicycle injury fell 73% between 2000 and 2012 (NYCDOT, 2013).

The City of Boston (2013) commissioned a report on bicyclist safety in 2013, which looked to understand how bicycling has changed since the start of the city's Boston Bikes program in 2007. Between 2007 and 2013, the city invested heavily into bicycle-related infrastructure, including more than 60 miles of bicycle lanes, 1,000 bicycle racks, and a bike share system. Further, the city also engaged in outreach events by providing bicycles to low income residents and bicycle training to the city's youth. Because of data reporting incompatibilities, the report was only able to show the change in bicycle use and injuries between 2010 and 2012. During this time period, bicycle exposure grew approximately 19%; however, bicycle-related injuries increased only approximately 6%. Extrapolating these values could show an approximate 29% increase in injuries for each doubling of bicycle exposure, and this value agrees with many studies on the SIN effect. However, it should be noted that the City of Boston is quite clear in its report that a SIN effect simply addresses the risk of a crash but does not necessarily influence the severity of that crash.

Marqués et al. (2014) studied the growth in bicycling in Seville, Spain, from 2006 to 2011. Among other findings, Marqués et al. noted that the ratio of bicycle-related crashes to bicycle volume decreased over the 5 years with the volume of bicyclists increasing nearly 590% while the number of reported crashes increased by only approximately 170%.

Schneider et al. (2017) compared pedestrian and bicyclist fatality rates for 46 of the largest metropolitan areas in the United States using Fatality Analysis Reporting System (FARS) and National Household Travel Survey data. Findings from this effort showed a SIN effect for both walking and bicycling when comparing proportion of trips taken and number of fatalities for a given mode.

Aldred et al. (2017) reviewed data from 202 local authorities in Britain to conduct both a cross-sectional (i.e., fixed point in time) and longitudinal investigation on the SIN effect. To complete this study, the researchers obtained data from several State-sponsored databases, including data on bicycle usage, motor vehicle usage, and crash data for fatalities and serious injuries. Data were collected for three time periods (1991, 2001, and 2011) to allow the longitudinal analysis. This study had several interesting findings. First, the authors defined the SIN effect as a non-linear relationship between the number of pedestrians or bicyclists and the number of











related fatalities and serious injuries. With this definition, the researchers found that a SIN effect is present in both cross-sectional and time-series data. From a longitudinal perspective, places where bicycling increased tended to have a decreased risk per bicyclist over time. Conversely, places where bicycling decreased, bicycling risk increased over time. The SIN effect was found to be stronger in the cross-sectional data as it appeared to weaken over time in the time-series data. Finally, despite the identified SIN effect, this research found that, over time, bicycling became relatively riskier compared both with motor vehicle use and walking. This is one of the only robust longitudinal studies in the SIN literature; however, it should be noted that the longitudinal aspect of this study is limited as it takes into account just three points in time.

Summary

A summary of the literature discussed in this section is presented in Table 9.

Table 9. Overview of Studies Covered in the Trend Analysis Section

Year	Author	Methodology	Objective	Road Users Studied	Results
2011	Tin et al.	Simple analysis	Assess regional variations in rates of traffic injuries to bicyclists resulting in death or hospital inpatient treatment based on time spent bicycling and time spent traveling in a motor vehicle.		Support SIN
2012	San Francisco Municipal Transportation Agency	Simple analysis	Document long-term collision trends and intersections with the highest citywide collision totals.		Refute SIN
2013	City of Boston	Simple analysis	Analyze bicyclist-related crash data.		Support SIN
2013	New York City Department of Transportation	Simple analysis	Document progress in making New York City streets safer, improving mobility, and maintaining and enhancing infrastructure.		Support SIN
2014	Marqués et al.	Simple analysis	Analyze the impact bicycle infrastructure development on urban mobility and bicycle traffic safety.		Support SIN
2017	Aldred et al.	Simple analysis	Examine cross-sectional and longitudinal SIN effects.		Support SIN
2017	San Francisco Municipal Transportation Agency	Simple analysis	Document long-term collision trends and intersections with the highest citywide collision totals.		Support SIN
2017	Schneider et al.	Simple analysis	Explore pedestrian and bicyclist fatality rates in 46 of the largest U.S. metropolitan statistical areas.		Support SIN

The studies presented in this section primarily use simple analyses (e.g., calculating and comparing historical averages, identifying trends) to investigate bicycle and pedestrian safety. Many of these studies compare exposure and safety and find that safety metrics (e.g., crashes)



do not increase at the same rate as exposure metrics (e.g., volume) and cite this finding as an example of the SIN effect.

Statistical Analysis and Modeling

Studies looking into the SIN theory used various statistical methods to model vulnerable road user crashes and other safety-related metrics. Of the many methods used, researchers commonly turned to negative binomial regression as the method of choice. The following sections discuss research using statistical analysis and modeling to better understand the SIN theory.

Bicyclists

Miranda-Moreno and Strauss (2011) developed an innovative model to describe bicyclist risk exposure using aggregated bicycle flows, motor vehicle flows aggregated by movement type (i.e., left-turn, right-turn, and through), and potential conflicts between motor vehicles and bicyclists for data from 753 signalized intersections in Montreal, Quebec, Canada. The researchers analyzed the data using negative binomial models and found that bicyclist safety at signalized intersections is significantly affected by bicyclist volumes and traffic flows, with the right-turning movements the most impacted. Model results showed that a 10% increase in bicycle flow through an intersection resulted in a 4.4% increase in the frequency of bicyclist injuries.

Building on this work, Strauss et al. (2013) used newer data from Montreal and a different modeling approach. Data from 647 signalized intersections were collected and a two-equation Bayesian modeling approach was applied to study bicyclist injury occurrence and bicycle activity at the signalized intersections. A SIN effect was found when model results showed that corridors with high bicycle volumes have lower risk of injury. However, it should be noted that while the model results found that these corridors have a lower individual risk, they are associated with a greater number of injuries. Similar to the team's previous work, bicyclist volumes were again found to have a strong association to bicyclist injury; a 1% increase in bicyclist volumes increases the expected number of bicyclist injuries by 0.87%.

Using negative binomial regression and national datasets of crashes and exposure, Schepers (2012) examined the relationship between single-bicycle crashes and bicycle kilometers traveled in the Netherlands. Schepers found that at the regional level, the increase in the number of single-bicycle crashes in a given area is proportionally less than the increase in the number of bicycle kilometers traveled. The negative binomial model developed to highlight this relationship as a power curve shows that the number of injuries due to single-bicycle crashes will increase at roughly 0.75 power of the number of kilometers traveled by bicycle. Schepers tempered the study results by describing the state of bicycling in the Netherlands; typically, the Dutch ride a bicycle for utilitarian purposes (e.g., commute) and start at a younger age than



many other countries. As such, Schepers noted that findings from this study may not be applicable in countries that do not share similar bicycling characteristics.

Another technique during this time considered law enforcement crash report data. Prato et al. (2015) analyzed the factors contributing to increased crash risk while riding a bicycle by

Crash rates decrease as bicycle traffic increases (Prato et al., 2015).

reviewing 5,349 law enforcement reported bicyclist-related crashes within 269 traffic zones in the Copenhagen region. Six Poisson-based models were developed using traffic, crash, and demographic data for the region. The Poisson-lognormal model with second-order spatial correlation effects performed best. This

model found a non-linear relationship between bicyclist-related crashes and average bicycle traffic in a zone, indicating that crash rates decrease as the average bicycle traffic increases, supporting the SIN theory. The model also found a non-linear relationship between motor vehicle volumes and number of pedestrian-related crashes showing that as the traffic volume increases in a zone, the number of pedestrian-related crashes decrease. The authors provided a possible explanation of this finding in that congestion builds as traffic volumes increase causing a decrease in traffic speeds thus providing more time for drivers to recognize potential conflicts.

Yao and Loo (2016) used exposure, land use, and demographic data to show a SIN effect at the local level (e.g., between neighborhoods). To do this, the researchers estimated bicycle trips at the smallest planning unit available for Hong Kong based on household travel survey data. This research found the significant predictors of a bicycle-motor vehicle crash were: bicycling exposure, vehicle flow, residential area, proportion of children 14 and younger, and median household income. The resulting negative binomial regression model included an exponent of 0.2, which is lower than the exponent found on most other SIN studies (typically around 0.5). This difference can be explained by the fact that bicyclist exposure was modeled with other variables (e.g., residential area variable); removing the additional variables yields an exponent of 0.37 and 0.33 (depending on period of data used). Yao and Loo hypothesize that this difference may show that using additional controlling variables may better describe the SIN effect as more of the model variation can be described by the other variables (e.g., infrastructure, environment, demographics) and less by bicyclist or pedestrian volume.

Thompson et al. (2016) used Rescorla–Wagner models in an attempt to explain any behavioral changes due to the presence of bicyclists. These models, developed by Rescorla and Wagner in 1972, explain the learning curve when pairing unconditioned and conditioned stimuli. This study developed an agent-based simulation of a city network for 2,000 motor vehicles shared with 50 bicyclists. In addition to the typical variables required for a microsimulation (e.g., network information, maximum speed), this model also included information on driver and bicyclist behavior (e.g., memory span, awareness). The modeling results of this study were able to replicate a SIN effect and, further, the researchers were able to control this effect with the simulation's behavioral factors. These factors were: bicycle saliency (e.g., a factor between 0 and 1 describing the extent to which bicycles on the road were observed by drivers), road saliency



(e.g., a factor between 0 and 1 describing the extent in which bicyclists' paths were observed by drivers), intention to drive safely, capacity to drive safely, memory span, and bicycle density. Results from this study are directly applicable to policy development and planning as they support the development of both educational and infrastructure improvements.

While many studies up to this point focused on exposure, Osama and Sayed (2016) focused on attributes of the Vancouver, Canada, bicycle network to develop a macro-level crash model. This model included variables of exposure, connectivity, route directness, and route topography to estimate bicyclist-related crashes. The model results were similar to past work that found a non-linear relationship between exposure variables and bicyclist-related crashes. The resulting model with the best fit found that the bicycle exposure variable (bicycle kilometers traveled) had an exponent of 0.46 and the vehicle exposure variable (vehicle kilometers traveled) had an exponent of 0.39. Findings related to the built environment showed that network density had a positive association with crashes while network continuity had a negative association. In other words, the models showed that bicycle networks with longer stretches of uninterrupted bicycle facilities would be safer than those with many intersections or other interruptions.

Other studies looked particularly at infrastructure factors. Wang et al. (2016) used data from Minneapolis, Minnesota, that focused on bicyclists. For this study, the researchers both estimated and collected peak-hour bicyclist traffic volumes and combined this with other data (e.g., infrastructure data, vehicle volumes, demographics) to model bicyclist crash risk. Three of the four resulting models confirmed the presence of a SIN effect where there were lower crash rates at areas of higher bicyclist traffic volumes. Several built environment variables were found to be significant in the resulting models. Variables describing trail crossings and commercial land use were found to be positively correlated to crashes while number of intersections within a 400-meter buffer of a given intersection was found to be negatively correlated to the number of crashes.

Meade et al. (2017) conducted research to answer the questions 'who is safe in numbers?' and 'where?' using data from Edinburgh, Scotland. Basic data on bicyclist distance traveled, motor vehicle distance traveled, and bicycle-related fatalities from 2001 to 2003 and 2010 to 2012 were obtained from State maintained databases. Data were aggregated to Scottish local governments known as council areas, and negative binomial models were fitted. The researchers found the exponent for the bicyclist exposure to be 0.68 and 0.71, respectively, for the first and second time periods in the data. These findings were similar, but slightly higher (i.e., less reduction in risk) than previous research. However, it should be noted that this study focused only on fatalities where others often include injuries as well. A second set of negative binomial regression models were developed to include both bicyclist and motor vehicle exposure variables, and again the exponents for these variables were found to be roughly in line with previous research. These results show that there is not a significant change in the SIN effect over time in the Edinburgh data. Researchers did find differences when looking across the council areas; the SIN effect was found to be weaker in rural areas.



Carlson et al. (2017) developed crash risk models using estimated bicyclist activity data from Minneapolis along with crash data and observed motor vehicle volumes. Because many of the intersections within the study area had no crashes during the study period, the researchers used a two-part model comprised of probit regression for the first part (the probability of any crashes) and Poisson regression for the second-part of the model (how many crashes among those predicted to have more than zero). Results from this study supported the SIN theory and found that every percentage increase in annual daily bicycle traffic increased the probability of a crash by 0.09% and the number of crashes by 0.50%. It should be noted that the authors indicate that the first part of the model had an accuracy of 52% (i.e., performs only slightly better than an uniformed guess when determining if a crash occurs at an intersection), and the second part of the model predicted the number of crashes with an 82.6% error on average (i.e., of those intersections that experienced crashes, the average difference between the actual and expected number of crashes was 82.6%). Thus, while this study supports the SIN theory, the resulting model accuracy and error do not provide strong support to the theory.

Marqués and Hernández-Herrador (2017) expanded their earlier study using trend analysis into bicycling in Seville, Spain, to include data from 2000 to 2013. This time span provided 7 years of data before and after the city built a network of segregated bicycle tracks through the city. The data used in this study included crash data, estimated number of bicyclist trips and length of bicycle tracks. While the researchers found that when modeled in a non-linear form, the exponent for bicyclist exposure was the same value as Jacobsen's original value (0.4) (Jacobsen, 2003), there were limitations to this research. In terms of the analysis, Marqués and Hernández-Herrador defined risk of bicycling as the number of collisions between bicycles and motor vehicles per million bicycle trips, as opposed to the number of collisions per cycled kilometer. Further, this study used only simple linear regression and did not model the number of crashes as a function of the number of bicyclists. Finally, in terms of the data, there was a large increase in the length of protected bicycle tracks near the middle of the study period that could have affected the results.

Ramsey and Richardson (2017) studied the SIN effect using data from travel surveys to estimate trip routes for exposure and used both law enforcement-reported crash data and hospital injury data to determine the number of injuries and fatalities. They highlighted large discrepancies between the law enforcement reported crash data and the hospital data. Over the same 7-year study period, the law enforcement reported data included only about a quarter of the number of serious injuries as the hospital data (2,677 versus 9,542). The researchers found mixed results when combining data into large groups based on proximity to the city center. One result showed that the areas closest to the city center were safer than the others, but this finding was weak. Next, the researchers pooled the data and reviewed kilometers cycled and serious injuries/fatalities. Findings from this second analysis showed a linear relationship between exposure and safety, indicating that there was no SIN effect in the data.



Pedestrians

Elvik et al. (2013) studied 316 crashes that occurred over 5 years near 159 marked pedestrian crossings in Oslo, Norway. The researchers used negative binomial regression to analyze several factors: volume of pedestrians and vehicles, the number of traffic lanes at the crossing, the location of the crossing (midblock or junction), the type of traffic control, the share of pedestrians using the crossing, and the speed of approaching vehicles. Findings from this analysis support the SIN theory finding that for each 100% increase of pedestrian volume, the total number of crashes near the crosswalk increases approximately 24% and those pedestrian crossing-related crashes increase by 69%.

For each 100% increase of pedestrian volume, the total number of crashes increases approximately 24% and pedestrian crossing-related crashes increase by 69% (Elvik et al., 2013.)

In the same year, Coughenour et al. (2013) used zero-inflated negative binomial regression analysis to study law enforcement reported pedestrian crash data collected from January 2009 to December 2011 (n=1,467) as well as census tract socioeconomic variables for Clark County, Nevada. The researchers did not include any variables for pedestrian exposure. Findings from this study shed light on when, where, and what factors influenced crashes in the study area. Specific to the SIN effect, Coughenour et al. found that pedestrian crashes were inversely related to population density.

Geng (2014) studied data from Austin, Texas, to quantify pedestrian crash risk and identify hotspot locations for pedestrian-related crashes. Crash data, land use data, road network data, motor vehicle volumes, and pedestrian volumes were used. Using negative binomial regression, Geng found four variables that were significantly related to pedestrian crash risk: average block length, posted speed limit, sidewalk condition, and the degree of proximity to major pedestrian attractors (e.g., bus stops, gas stations with grocery stores). Specific to the SIN effect, Geng found that the degree of proximity to major pedestrian attractors increased the likelihood of a pedestrian-related crash, refuting the idea that increased numbers of pedestrians will increase safety. A potential explanation for this finding is the possibility that tourists, unfamiliar with the area, made up a disproportionate number of these pedestrian crashes.

Murphy et al. (2015) evaluated whether the SIN phenomenon is observable in both originally collected data and an extrapolation model of Minneapolis. For this effort, researchers developed a linear regression model to estimate pedestrian volumes using census-block level information regarding: economic accessibility, trip distance, public transit information, and Average Annual Daily Traffic (AADT). Further, researchers manually conducted traffic counts for comparison and validation purposes. Murphy et al. found the SIN effect present in both the modeled and observed data where intersections with higher pedestrian traffic exhibited lower per-pedestrian crash rates. Wang, Lindsey, and Hankey (2016) subsequently conducted a similar study of bicyclists reported in the previous section.



In 2017 Murphy et al. continued to look into SIN by studying a sample of 488 intersections in Minneapolis. For this effort, the researchers only looked at intersections with pedestrian counts, unlike the previous effort where some of the data were modeled. Diverging from previous studies, the researchers used a log-linear model in lieu of a negative binomial model as the per-user crash rates appeared to follow negative exponential decay and were not integer count values. Findings from the study found a SIN effect both for pedestrian-motor vehicle crashes as well as for motor vehicle only crashes. Murphy et al. hypothesized that finding both a SIN effect for pedestrians-related crashes and for motor vehicle-related crashes could hint that motorists drive more cautiously when there are more motor vehicles present as well as when there are more pedestrians present. The researchers noted that the SIN effect was found to be stronger for the pedestrian-related crashes.

Omer et al. (2017) used network, land use data, and observed traffic data to estimate pedestrian volumes and pedestrian crash risk for two cases studies containing a total of 979 street segments in Tel Aviv, Israel. The motor vehicle and pedestrian crash risks were estimated using negative binomial models. This study supports the SIN effect for pedestrian-related crashes; however, it does have some differences from other studies. First, there were differences between the two case studies conducted within this effort. For the first case study (Ibn Gabirol Street, a busy shopping and residential street), the function representing pedestrian risk had an inflection point where at low levels of pedestrian volume, pedestrian risk actually increased as pedestrian volume increased. While this same finding was not present in the pedestrian crash risk model for the second case study (Florentin neighborhood), the motor vehicle crash risk model also portrayed this behavior. A second interesting finding from this study was that when motor vehicle crash risk was modeled, the output showed a similar SIN effect, much like Murphy et al. (2017).

Bicyclists and Pedestrians

Several recent studies have considered both pedestrians and bicyclists operating in the same environment. For instance, Dumbaugh et al. (2013) used negative binomial regression to study the built environment (e.g., infrastructure, land use) to understand related causes of pedestrian- and bicycle-related crashes. The researchers used 5 years of data from the San Antonio–Bexar County region in Texas. Data used included crash data, land use data, road network data, and motor vehicle volumes. Pedestrian and bicyclist exposure data were not used in the model. Among the several findings, one in particular is specific to the SIN effect. Dumbaugh et al. found that population density had a positive, but weak relationship with total pedestrian crashes, no statistically significant relationship with pedestrian crashes resulting in a fatality or injury, and no statistically significant relationship with bicycle-related crashes resulting in a fatality or injury. Using population density as a proxy for pedestrian and bicyclist activity, this finding refutes the SIN effect, which would expect an inverse relationship between population density and crash risk.



Schepers and Heinen (2013) studied the effect of mode shift from motorized to non-motorized modes of transportation through the analysis of 6 years of data from 387 Dutch municipalities having more than 10,000 residents. This study is unlike many of the other studies related to the SIN theory because the data for this study contain information on injuries received from single-bicycle crashes. Negative binomial regression was used to develop crash prediction models. Findings from the study show that transferring trips from motor vehicle to walking or biking does not lead to a significant change in fatalities, but there will be an increase in serious bicyclist injuries due to single-bicyclist crashes. Schepers and Heinen state that given the high risk of walking or biking relative to driving a motor vehicle, this research does show a SIN effect because the number of fatalities does not increase.

Jonsson (2013) developed safety performance models for pedestrians and bicyclists based on data from two Swedish cities. The first dataset included 5 years of data from 400 urban street segments and the second had more than 5 years of data from 360 segments and 63 intersections. Both datasets included roadway characteristics, short (e.g., 15 minute) pedestrian counts, and crash information. Two modeling approaches, quasi-Poisson and negative binomial, were used to analyze the data. The two approaches and two datasets allowed Jonsson to develop models to describe motor vehicle and bicycle crashes, motor vehicle and pedestrian crashes, pedestrian-only incidents, and bicycle-only crashes. Jonsson reported that the hospital data used in this study included records for 497 single-pedestrian incidents (i.e., an injury to a pedestrian without presence of motor vehicle or bicycle) allowing the pedestrian-only model to be developed. Looking at model results, Jonsson found that all models except the pedestrian-only model show a SIN effect, with this effect stronger for bicyclists than pedestrians. Another interesting finding from this study is that the SIN effect is shown for bicyclist-only crashes, which cannot be explained by changes in driver behavior. This is opposed to the common explanation for the SIN effect that motorists are more aware of bicyclists and pedestrians in areas of high concentrations. The exponents developed as part of this study are shown in Table 10.

Table 10. Model Exponents for Pedestrian and Bicyclist Volumes From Jonsson (2013)

Model Type	Crash/Incident Type	Exponent	Statistically Significant
Quasi-Poisson	Motor vehicle and bicyclist	0.35	✓
Quasi-Poisson	Motor vehicle and pedestrian	0.5	✓
Negative binomial	Motor vehicle and bicyclist	0.201 to 0.334*	✓
Negative binomial	Motor vehicle and pedestrian	0.695 to 0.743*	✓
Negative binomial	Bicyclist only	0.104 to 0.342*	✓
Negative binomial	Pedestrian only	0.934 to 1.108*	
*Several models were developed based on roadway characteristics (e.g., number of lanes)			

Kröyer (2015) studied pedestrian- and bicycle-related crashes in six mid-size Swedish cities, with a median population equal to 96,906 residents. Kröyer analyzed crash and exposure data using multinomial logit models, negative binomial regression, and other statistical methods and found a positive correlation between the exposure of pedestrians, bicyclists, and motor vehicles and



the number of crashes. This correlation supports the SIN effort as it is non-linear, where the crash risk per road user is lower at sites where the exposure is greater.

Kröyer (2016) then conducted a study to develop safety performance functions for pedestrian and bicyclist crashes at urban intersections. Kröyer collected exposure and crash data from 113 intersections across six Swedish cities. Traffic volumes were collected from official datasets, and

The SIN effect is apparent in all models resulting from this analysis: single-pedestrian incidents, single-bicyclist crashes, pedestrian-motor vehicle crashes, and bicyclist-motor vehicles crashes (Kröyer, 2016).

3-hour manual counts were completed to gauge pedestrian and bicyclist volumes. The crash data in this study included hospital data, so crashes resulting in minor injuries typically not captured in law enforcement crash datasets were included in this analysis. Modeling results show that the SIN effect is apparent in all models resulting from this analysis: single-pedestrian incidents, single-bicyclist crashes, pedestrian-motor vehicle crashes, and bicyclist-motor vehicle crashes. Most of these findings are consistent with existing studies; however, the one previous study looking at SIN for single-pedestrian incidents (Jonsson, 2013) did not find a SIN effect. Kröyer speculated that the presence of a SIN effect for single-pedestrian incidents may be due to exposure serving as a proxy measure for the quality and availability of pedestrian-related infrastructure; in other words, areas where more pedestrians tend

to travel through will have more pedestrian-related infrastructure, and that infrastructure will be better maintained, thus preventing injuries. This study did include some geometric variables in the data; however, these variables were not found to be statistically significant.

Elvik (2016) used Norwegian data from 239 pedestrian crossings to show a very strong SIN effect for both pedestrians and bicyclists. In Elvik's final model, the coefficients for traffic volume were 0.05 for motor vehicles, 0.07 for pedestrians, and 0.12 for bicyclists. One difference in this work when compared to many other previous studies is that variables for motor vehicle, pedestrian, and bicyclist volume were included in the same model, whereas many other studies developed separate models to estimate collisions for each mode. However, Elvik pointed out that the model developed in this study accounted for only about 21% of the systematic variation in the number of crashes, and as such there were likely other variables that should be included in future studies to develop a more accurate model.

Tasic et al. (2017) found the SIN effect to be present at the macroscopic level for pedestrian-, bicyclist-, and motor-vehicle-related crashes using citywide data from Chicago, Illinois. For this study, Tasic et al. compiled a comprehensive dataset that included roughly 100 variables to describe travel demand, safety, and proxy measures for exposure that included the representation of multimodal infrastructure and accessibility. Data were analyzed at the census tract level (n=801) using generalized additive models (GAM). The models developed from this project included proxy variables for accessibility that can help planners and practitioners better understand how crash risk changes with different land uses and infrastructure. Variables that



represented roadway functional classification, conflict points, and intersection traffic control were found to increase the number of pedestrian crashes, and the variable for street connectivity was associated with a reduction of pedestrian crashes.

Summary

A summary of the literature discussed in this section is presented in Table 11. Most of these studies use some form of generalized linear modeling, with negative binomial regression being most common.

Table 11. Overview of Studies Covered in the Statistical Analysis and Modeling Section










Year	Author	Methodology	Objectives	Road Users Studied	Findings
2011	Miranda-Moreno & Strauss	Generalized linear models (negative binomial)	Detail a new approach to represent bicyclist risk exposure.		Support SIN
2012	Schepers	Generalized linear models (negative binomial)	Examine the relationship between bicycle use and the number of single-bicycle crashes (i.e., only one bicyclist involved).		Support SIN
2013	Pharr et al.	Generalized linear models (zero-inflated negative binomial)	Analyze pedestrian crash characteristics to determine if there is a significant relationship between pedestrian crashes and socio-economic variables.		Support SIN
2013	Dumbaugh et al.	Generalized linear models (negative binomial)	Explore how the characteristics of the built environment may affect the incidence of crashes involving pedestrians and bicyclists.		Refute SIN
2013	Elvik et al.	Generalized linear models (negative binomial)	Analyze factors influencing safety at marked pedestrian crossings.		Support SIN
2013	Jonsson	Generalized linear models (quasi-Poisson and negative binomial)	Explore crash prediction models for pedestrian- and bicyclist-related crashes.		Support SIN
2013	Schepers & Heinen	Generalized linear models (negative binomial)	Examine the road safety impact of a modal shift from short car trips to bicycling.		Support SIN
2013	Strauss et al.	Bayesian analysis	Simultaneously study bicyclist injury occurrence and bicycle activity at signalized intersections as joint outcomes.		Support SIN
2014	Geng	Stepwise bivariate analysis, generalized linear models (negative binomial)	Examine the association between pedestrian collision rate and independent variables (e.g., exposure, built environment).		Refute SIN



Table 11 (cont.). Overview of Studies Covered in the Statistical Analysis and Modeling Section
















Year	Author	Methodology	Objectives	Road Users Studied	Findings
2015	Kröyer	Generalized linear models (negative binomial)	Study the relationship between exposure and the risk in pedestrian- and bicycle-related crashes as well as how speed at the time of the crash affects crash outcomes.		Support SIN
2015	Murphy et al.	Linear regression (parsimonious)	Explore the SIN effect using a combination of estimated and collected data.		Support SIN
2016	Elvik	Generalized linear models (negative binomial)	Develop crash prediction models to explore the SIN effect.		Support SIN
2016	Kröyer	Generalized linear models (negative binomial)	Create crash prediction models for pedestrian and bicyclist crashes at urban intersections and to analyze the reliability of crash models based on short observational periods.		Support SIN
2016	Osama & Sayed	Generalized linear models (negative binomial) and full Bayesian	Study bicyclist-related crashes to assess the impact of bicycle network structure on bicyclist safety.		Support SIN
2016	Prato et al.	Generalized linear models (Poisson)	Study the factors affecting the probability of bicyclist–motorist collisions while accounting for heterogeneity and spatial correlation.		Support SIN
2016	Thompson et al.	Agent-based model	Explore the potential role of behavioral adaptation of drivers to the presence of bicyclists that followed patterns of Rescorla–Wagner learning models.		Support SIN
2016	Wang et al.	Logistic regression (Firth)	Estimate the probability of crashes at intersections and on street segments and assess the effects of built environment variables on the probability of bicycle crashes.		Support SIN
2017	Carlson et al.	Probit models, generalized linear models (Poisson)	Assess the estimated crashes per bicyclist and per vehicle as a function of bicyclist and vehicle traffic, and test whether greater traffic reduces the per-car crash rate.		Support SIN
2017	Marqués & Hernández-Herrador	Multiple linear regression analysis	Analyze the risk of bicycling before and after the implementation of a network of segregated cycle tracks.		Support SIN
2017	Meade et al.	Multivariate regression analysis	Explore the spatial distribution of SIN to ask, "who is safe in numbers?" and "where?".		Support SIN



Table 11 (cont.). Overview of Studies Covered in the Statistical Analysis and Modeling Section

Year	Author	Methodology	Objectives	Road Users Studied	Findings
2017	Murphy et al.	Log-linear regression	Develop relationships between pedestrian traffic flows and the per-pedestrian crash risk.		Support SIN
2017	Omer et al.	Space syntax, generalized linear models (negative binomial)	Investigate the spatial distribution of vehicle and pedestrian crashes relative to the volume of vehicle and pedestrian movement in urban areas.		Support SIN
2017	Ramsey & Richardson	Linear regression	Determine how levels of bicycle activity affect the risk of injury to each bicyclist.		Both Support and Refute SIN
2017	Tasic et al.	Generalized linear models (generalized additive model)	Explore safety in numbers effect for bicyclists and pedestrians in areas with different levels of access to multimodal infrastructure.		Support SIN

Behavioral Research

While the majority of SIN literature focused on the statistical relationship between exposure and safety, a few researchers focused efforts on exploring behavioral factors related to the theory. In this research, interviews and surveys frequently served as a source of data to better understand pedestrian and bicyclist behavior, experiences, and opinions.

De Geus et al. (2012) used weekly travel diaries and questionnaires to collect bicycle travel and injury data across Belgium for 1 year, resulting in data from 1,847 people representing approximately 215,000 bicycle trips over nearly 1.5 million kilometers (~0.9 million miles). It is important to note that for this project, injuries were not confined only to those involving a motor vehicle; any injury more serious than a muscle cramp or bruise received while riding a bicycle for utilitarian purposes (e.g., commute to work) was included in the data. The team calculated the overall injury rate for reported crashes to be 0.324 per 1,000 trips (95% CI 0.248–0.400), 0.896 per 1,000 hours (95% CI 0.686–1.106), and 0.047 per 1,000 kilometers (~621 miles) (95% CI 0.036–0.059) of exposure. When grouping participants by region, the researchers found that the region with the highest reported bicycle use had the lowest injury rate, providing support to the SIN theory.

Fyhri and Bjørnskau (2013) conducted a controlled investigation of the SIN effect using interviews with bicyclists, pedestrians, and car drivers at three points of time in Oslo, Norway. The team asked participants (n=1,560) questions about their travel behaviors and interactions between motor vehicle, bicyclists, and pedestrians. The team's hypothesis for this study was that SIN is based on motorists observing greater numbers of pedestrians and bicyclists and adjusting their driving behavior. To test this hypothesis, the team gauged participant opinion on the



frequency they had been seen (or not seen) by drivers at three points in the year. After controlling for different factors (e.g., seasonal variation, bicyclist types), the researchers found that interview results supported the existence of a SIN effect among bicyclists, but not pedestrians. Specifically, the frequency bicyclists reported being seen by drivers increased as the volume of bicyclists increased.

Bicyclists reported being seen more commonly by drivers when there were more bicyclists on the road (Fyhri et al., 2014).

Fyhri et al. (2014) continued this work by conducting a similar survey in Norway and Denmark. Findings from the expanded survey confirmed findings in the previous work and again showed that drivers are more attentive to bicyclists as the number of bicyclists increase. An interesting finding is that bicyclists reported being seen more commonly by drivers when there were more bicyclists on the road, and at the same time drivers did not report a significant change in how often they were “surprised” by the presence of a bicyclist regardless of bicyclist volumes. The combination of these

two findings could provide support to the thought that drivers are changing their behavior when there are more bicyclists present.

Fyhri et al. (2017) next built off of previous work to include video observations, additional survey data, and crash data. This crosscutting study again looked at seasonal differences in how bicyclists and drivers interact, and compared populations of bicyclists in Norway, Denmark, and Sweden. Both the survey data and video observation data lent support to the SIN effect; however, the researchers did find differences when comparing data across countries. While in-depth analysis of crash data was not completed for this study, an exploratory analysis of the data did seem to add support for the SIN effect as well. Comparing across the three countries, it appears that infrastructure and traffic culture affect the strength of the SIN effect. For example, this study found that bicyclists in Denmark were more obedient to road rules than those in Sweden and Norway; however, researchers also point out that common bicycle-related infrastructure in Denmark has more conflict points than similar infrastructure in other countries. While this study does seem to show a link between traffic culture, infrastructure, and SIN, the available data do not explain this link.

Like Fyhri and Bjørnskau (2013), Johnson et al. (2014) also conducted a survey to understand driver and bicyclist experiences. Citing a hypothesis of Jacobsen (2003) and others that when the population of bicyclists increases, it means more drivers are also bicyclists and therefore are more knowledgeable about bicyclists’ behaviors and more willing to accommodate bicyclists. The team looked to determine any differences in self-reported driving behaviors of bicyclists and non-bicyclists. For this research, the team conducted an online survey of Australian drivers (n=1,984) and compared responses between those who are both bicyclists and drivers and those respondents that did not ride a bicycle. Findings from this study do show differences in the populations. Those participants that both cycled and drove were 1.5 times more likely than drivers to report safe driving behaviors related to sharing the roads with bicyclists (95% CI: 1.1–



1.9, $p < 0.01$). These bicyclist-drivers had better knowledge of the road rules related to bicycling infrastructure than drivers. Drivers that did not ride bikes were more likely than bicyclist-drivers to have negative attitudes about bicyclists. In addition to highlighting the need to educate non-bicyclists on best practices for sharing the road, this study highlighted the need for more education on laws and best practices for bicycle-related infrastructure as knowledge on this topic was low for both groups.

Jacobsen et al. (2015) revisited the SIN theory and conducted a literature review to discuss road user behavior and its linkage to the SIN theory. They laid out several hypotheses for changes in vulnerable road user behavior to explain the theory (e.g., traveling in clusters), but concluded that hypotheses about changes in vulnerable road user behavior are unlikely a major cause of the effect. Jacobsen et al. described hypotheses for changes in driver behavior to explain the SIN effect (e.g., “looked, but failed to see”) and concluded that it is possible that drivers “learn to see” vulnerable road users as they become more accustomed to driving in the presence of these road users.

Other Research With Implications for SIN

In addition to the work cited above, many other researchers have looked into the behavioral aspects of pedestrian and bicyclist safety outside of the realm of SIN, and some of these studies produced findings related to SIN. For example, while a study evaluating bicyclists’ preferences or experiences with encouragement campaigns may not be directly related to SIN, if findings from such a study showed that specific campaigns increased ridership, the study would be indirectly related to the topic. Three main themes were identified in this type of literature: studies assessing effectiveness of pedestrian or bicyclist improvements and programs, studies investigating pedestrian and bicyclist preferences, and studies investigating differences in bicyclist behavior based on different levels of experience.

Rissel and Garrard (2006) studied the effectiveness of programs to promote bicycling in Australia and found that nearly all identified bicycling promotion program evaluations have shown some degree of increase in bicycling. Cinnamon et al. (2011) focused on the behavioral aspect of pedestrian-related crashes and discussed how behavioral-focused injury interventions are rare compared to engineering solutions, but can be more effective when properly planned and implemented. Finally, Monsere et al. (2014) evaluated protected bicycle lanes in five U.S. cities in terms of their use, perception, benefits, and impacts using video, surveys, and count data. The consensus from bicyclists across all study sites was that protected lanes improved bicyclists comfort and encourage ridership. Quantitatively, the bicycle lane implementations all showed an increase in ridership greater than the overall increase in the community.

Daley et al. (2007) conducted focus groups to understand the barriers and influences to bicycling by people with varying level of bicycling experience in Sydney, Australia. This study showed that riders of all levels of experience agreed that improved bicycle infrastructure would be a significant enabler to bicycling, with many indicating that available bicycle infrastructure



was necessary for increasing ridership. In addition, focus group participants also agreed that they felt a greater safety riding with others. Brick et al. (2011) conducted a large survey to better understand the behavior and preferences of bicyclists in Ireland (n=1,941). Relevant findings from this survey showed that while pedestrians preferred routes with light pedestrian traffic, bicyclists preferred those routes with heavy bicycle traffic. Rybarczyk and Gallagher (2014) collected surveys from 110 participants to determine strategies to increase bicycling and walking in Flint, Michigan. One of the main takeaways from the survey results was that bicyclists and pedestrians seek safe routes, and strategies to improve safety are desired. Another interesting finding was that many potential bicyclists indicated that they would be encouraged to commute via bicycle if they saw more bicyclists in the community.

Several researchers have looked to understand how differing levels of experience shape bicyclist behavior. Washington County, Oregon (Oylear et al., 2012) conducted randomized surveys (n=1,300), listening sessions, and a literature review to understand health outcomes and determinants related to bicycling and found that novices and those bicyclists with limited experience prioritized the need for bicycle infrastructure that separates bicyclists from motor vehicle traffic, while those more experienced riders identified bicycle lanes as a higher priority. Bill et al. (2015) administered an online survey to commuter bicyclists and others who were considering bicycling to work. Finally, Johnson and Chong (2015) studied the behaviors of those drivers who also rode and highlighted that those drivers likely to have a better understanding of how to interact with bicyclists than drivers without bicycling experience.

Summary

A summary of the literature discussed in this section is presented in Table 12. The studies that focused on the behavioral aspect of pedestrian and bicycle safety typically relied on input from riders and pedestrians (e.g., surveys, interviews). Findings from these studies help describe the SIN effect, but unlike many of the studies that developed crash prediction models, these studies less commonly support or refute the SIN theory directly.

Table 12. Overview of Studies Covered in the Behavioral Research Section













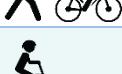


Year	Author	Methodology	Objective	Road Users Studied	Findings
2006	Rissel & Garrard	Literature review	Review unpublished 'gray' Australian literature that addresses the promotion of bicycling, and that has an evaluation component that allows the identification of effective interventions or factors that influence population levels of bicycling.		Neither Support nor Refute SIN
2007	Daley et al.	Focus groups	Explore factors that influence personal decisions to initiate and maintain bicycling and to identify differences in bicycling behavior.		Neither Support nor Refute SIN
2011	Brick et al.	Surveys	Examine infrastructure preferences for bicyclists.		Neither Support nor Refute SIN



Table 12 (cont.). Overview of Studies Covered in the Behavioral Research Section

Year	Author	Methodology	Objective	Road Users Studied	Findings
2011	Cinnamon et al.	Simple analysis	Examine the potential association between violations made by pedestrians and motorists at signalized intersections, and collisions between pedestrians and motor-vehicles.		Neither Support nor Refute SIN
2012	de Geus et al.	Questionnaires	Gain insight into bicycle crashes.		Support SIN
2012	Oylear et al.	Surveys, listening sessions, interviews	Research the connections between health, built environment design and transportation policies as well as barriers to active transport.		Neither Support nor Refute SIN
2013	Fyhri & Bjørnskau	Interviews	Test the existence of the SIN effect through the use of interviews with bicyclists, pedestrians, and drivers between the seasons.		Support SIN
2014	Fyhri et al.	Surveys	Build on previous work and test the existence of the SIN effect through the seasons using surveys with bicyclists, pedestrians, and drivers.		Support SIN
2014	Johnson et al.	Surveys	Analyze self-reported behavior, attitudes, and knowledge in relation to bicycling.		Neither Support nor Refute SIN
2014	Monsere et al.	Video data, surveys	Examine protected bicycle lanes using video, surveys of intercepted bicyclists and nearby residents, and count data.		Neither Support nor Refute SIN
2014	Rybarczyk & Gallagher	Surveys	Ascertain what travel demand management strategies will increase bicycling and walking activity.		Neither Support nor Refute SIN
2015	Bill et al.	Surveys	Investigate perceived risk of bicycling among two groups: experienced bicyclists and a combined group of novice and intermediate bicyclists.		Neither Support nor Refute SIN
2015	Jacobsen et al.	Literature review	Investigate the cause of the SIN effect.		Support SIN
2015	Johnson & Chong	Video data	Study bicyclist behavior on trips to and from their place of employment.		Neither Support nor Refute SIN
2017	Fyhri et al.	Surveys, video data	Build on previous work and test the existence of the SIN effect through the seasons using surveys with bicyclists, pedestrians, and drivers as well as video data.		Support SIN

Methodological Assessment

Any investigation of the SIN concept will be challenging due to the difficulties in measuring risk and exposure and to addressing potential sources of bias. The nature of this research, examining real world behavior with few controls, allows it to be studied with different units of observation, data sources, and modeling approaches. To consider these differences, an in-depth methodological assessment was conducted for 50 resources rated highly by reviewers (e.g., high relevance to SIN, data-driven) during the critical review to identify trends and gaps in the method and data used in the SIN literature.



Methodological Choices

In conducting SIN research the methodology selected can lead to challenges to the validity and reliability of the results. Methodological shortcomings were apparent in 6 studies. Two studies did not quantify the relationship between crashes and exposure, and instead graphed the relationship and fit an exponential curve to the data (Bonham et al., 2006; Murphy et al., 2015). The SIN effect described in another study was highly confounded with a large increase in segregated bicycle track lengths (Marqués & Hernández-Herrador, 2017). The fourth study modeled the probability of crashes at intersections and on street segments rather than the number of crashes (Wang et al., 2016).

The most serious shortcomings were found in 2 studies where the authors modeled crash *risk* as the dependent variable (Murphy et al., 2017; Schneider et al., 2017). Measuring risk as the number of injuries per distance walked and exposure as the distance walked per inhabitant, “can generate a spurious negative relationship between exposure and risk that looks like a safety-in-numbers effect” (Elvik, 2013). Murphy et al. (2017) defined pedestrian risk as “the number of crashes...divided by the...count of pedestrians” and Schneider et al. (2017) calculated pedestrian and bicyclist fatality rates within metropolitan statistical area populations. Both studies found the expected negative relationship.

Data Elements

Safety and exposure data are minimum requirements for investigating SIN. Some researchers (Elvik et al., 2013; Omer et al., 2017) considered all crashes (including single-road-user crashes), while others focused on crashes between motor vehicles and pedestrians or bicyclists. The number of motor vehicle-bicyclist crashes was the most widely studied type of crash. In some cases, several years of crash data were averaged to produce a more representative sample; Kaplan and Prato (2015) and Yao and Loo (2016) averaged 5-year and 3-year periods, respectively. Table 13 summarizes the types of data used in the 20 studies reviewed involving real-world analyses (i.e., excluding simulations, surveys, and meta-analyses).



Table 13. Data Types Used in 20 Real-World Analyses of SIN

Data Type		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	Total
Safety	Total crashes	○	○	○	○	○	●	○	○	○	○	○	○	○	○	○	○	○	○	○	○	2
	All bicyclist crashes	●	○	○	○	●	○	○	○	○	○	●	○	○	○	○	○	○	○	○	○	3
	All pedestrian crashes	○	○	○	○	●	○	○	○	○	○	○	○	○	●	○	○	○	○	○	○	2
	Severe bicyclist crashes	○	○	○	○	●	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	1
	Severe pedestrian crashes	○	○	○	○	●	○	○	○	○	○	○	○	○	●	○	○	○	○	○	○	2
	# of bicyclist-motor vehicle crashes	○	●	●	●	○	○	●	●	●	○	○	○	○	○	○	○	○	○	○	○	10
	# of pedestrian-motor vehicle crashes	○	●	○	○	○	●	○	●	●	○	○	○	○	○	○	○	○	○	○	○	7
	# of fatalities or serious injuries	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	3
Cyclist Exposure	Counts	○	○	●	○	○	○	○	●	●	○	○	○	○	○	○	○	○	○	○	○	5
	Time	●	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	3
	Distance	●	○	○	●	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	6
	Trips	●	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	2
	Turning movement counts	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	2
Pedestrian Exposure	Counts	○	●	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	8
	Trips	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	1
Motor Vehicle Exposure	Counts	○	●	●	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	6
	Time	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	2
	Distance	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	11
	Turning movement counts	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	1
Other Exposure	Bicyclist x motorist distance	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	1
	Bicyclist x pedestrian counts	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	1
	Motorist distance x bicyclist trips count	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	1
	Length of tracks or links	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	5

1. de Geus et al., 2012
2. Kröyer, 2015
3. Strauss et al., 2013
4. Osama & Sayed, 2016
5. Tasic et al., 2017
6. Elvik et al., 2013
7. Prato et al., 2015
8. Kröyer, 2016
9. Turner et al., 2006
10. Tin et al., 2011

11. Yao & Loo, 2016
12. Geyer, Pham, et al., 2006
13. Jonsson, 2013
14. Elvik, 2016
15. Kaplan & Prato, 2015
16. Aldred et al., 2017
17. Carlson et al., 2017
18. Meade et al., 2017
19. Omer et al., 2017
20. Turner et al., 2009



Safety Data

Crash data were often sourced from official government statistics. These databases are generally considered reliable but rely on bicyclists and pedestrians to report crashes in which they are involved. Several studies commented on the underreporting of less severe crashes. Turner et al. (2006) compared bicyclist and pedestrian crash reporting rates among three databases and found that some databases contained little more than half the crashes of others. Indeed Turner et al. (2009) cite a study conducted by the Christchurch Cycle Safety Committee (1991) relaying that “a study of cyclists with 1,400 responses from adult cyclists and 3,500 responses from school children found that the reporting rate for all cyclist crashes is approximately 21%” (Turner et al., 2009, p. 49). Kaplan and Prato (2015) excluded crashes involving a bicyclist alone or colliding with another vulnerable road user due to the “severe under-reporting of these types of crashes in police records in Denmark” (p. 4). To overcome the problem of underreporting, Strauss et al. (2013) used ambulance data instead of law enforcement report data, noting that “ambulance data may be biased towards more severe injuries [but], in Montreal, this source of data identified more bicyclist injuries than police reports” (p. 13).

Exposure Data

Exposure can be measured in several ways for each road user group, as summarized in Table 13. Bicyclist exposure was measured in five different ways: counts, distance, time spent bicycling, number of trips made by bicycle, and turning movement counts. The most widely used metric was distance cycled in a given time period. Two studies (de Geus et al., 2012; Aldred et al., 2017) restricted exposure to commuters (“utilitarian bicycling”). Pedestrian exposure was expressed as counts or trips. Motor vehicle exposure was most often measured in distance traveled, but was also measured in vehicle counts, time, and turning movement counts. Three studies (Osama & Sayed, 2016; Tasic et al., 2017; Elvik et al., 2013) used products of two exposure measures. Tasic et al. (2017) justified this technique by the assumption that “if either of these two variables...is equal to zero, no pedestrian crashes would be expected.” Among some studies focusing on roadway segments, segment length was also included as an exposure metric.

Counts were made in a variety of ways. The duration of on-site counts ranged from “[5] minutes for each hour” (Omer et al., 2017) to 15 minutes (Jonsson, 2013; Turner et al., 2009), 30 minutes (Fyhri et al., 2017; Turner et al., 2009), 6 hours (Elvik, 2016), and 12 hours (Aldred et al., 2017). One study analyzed the effect of count observation length on the stability of parameters in a negative binomial regression framework and found that shorter observation times lead to “a systematic underestimation of the parameters for pedestrian and bicyclist flows and an overestimation of the parameter for the flow of motorized vehicles,” noting that “the parameters are within the confidence interval of the [models with longer counts]” (Kröyer, 2016). Two studies used automated methods: vehicle counters (Geyer, Pham, et al., 2006) and video footage (Fyhri et al., 2017).



Steps were taken to ensure the representativeness of counts made. Some counts were made during peak hours (Turner et al., 2006; Carlson et al., 2017) while others (Kröyer, 2015, 2016; Omer et al., 2017) avoided these times “because the peak hour for pedestrians and bicyclists can be very brief and extreme” (Kröyer, 2015, p. 35). Two studies used the same bicyclist count data “collected during university and school holidays,” noting the expected underestimation of average bicycle flows (Turner et al., 2006, p. 61; Turner et al., 2009, p. 54). Counts were often made only on weekdays with optimal weather and no rain. Adjustments to counts were made in a number of studies. Short counts were converted to annual average daily values using “temporal and weather adjustment factors” (Strauss et al., 2013; Turner et al., 2006), and “bicyclist traffic count factors” (Carlson et al., 2017).

Researchers identified a variety of data sources, including manual traffic counts, pre-existing data, and modeled data using existing data and established traffic models. For instance, Kröyer (2016) estimated flows at intersections where no data were available “based on the number of houses, land use, and road network.” On a larger scale, Geyer, Pham, et al. (2006) employed the space-time path method by calculating the shortest path between origin-destination pairs.

Other Explanatory Data

In addition to crash and exposure data, some studies included other potential explanatory variables in their statistical models, as summarized in Table 14. Seven studies included land use variables, but only four found significant effects on crash counts. Findings included, “bicycle paths are less effective in suburban areas” (Prato et al., 2015, p. 10), areas with “more residential land use...had greater numbers of bicycle collisions” (Yao & Loo, 2016, p. 383), “intersections in commercial and mixed use (residential and commercial) [areas had] increased risk [of pedestrian crashes] compared with intersections in residential neighborhoods” (Geyer, Pham, et al., 2006, p. 153), and “city center and industrial zones are related to a higher number of [bicycle] crashes” (Kaplan & Prato, 2015). Kröyer (2016) included geometric variables on a theoretical basis, even though none of the variables were found to be statistically significant.

Table 14. Inclusion and Findings Regarding Potential Explanatory Variables in Statistical Models

Explanatory Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Land use	○	◐	○	○	○	○	●	◐	○	○	●	●	◐	○	●	○	○	○	○	○
Built environment	○	◐	●	●	●	●	●	◐	○	○	○	◐	○	◐	●	○	○	○	◐	○
Demographics	○	○	○	○	○	○	●	○	○	○	◐	○	○	○	○	◐	○	○	○	○

Notes:

Refer to Table 13 for the list of study authors.

○ indicates an explanatory variable was not included in statistical models,

◐ indicates it was used but not found statistically significant, and

● indicates it was used and found statistically significant.



Six of 11 studies that included data on the built environment found significant effects. Longer crosswalks (Strauss et al., 2013), higher number of intersections within a given area (Osama & Sayed, 2016; Tasic et al., 2017), signalized intersections (Tasic et al., 2017; Elvik et al., 2013; Kaplan & Prato, 2015), a greater concentration of locations accessible by bicycle (Tasic et al., 2017), more bike lanes (Tasic et al., 2017), more legs at crossing locations (Elvik et al., 2013), yield- or stop-controlled intersections (Kaplan & Prato, 2015), and roundabouts (Kaplan & Prato, 2015) were associated with more crashes of various types. Fewer crashes were associated with curb extensions (Strauss et al., 2013), raised medians at intersections (Strauss et al., 2013), street connectivity (Tasic et al., 2017), the number of driving lanes at crossing locations (Elvik et al., 2013), and bicycle facilities (Prato et al., 2015; Kaplan & Prato, 2015). Notably, one study found that the presence of a bus stop at an intersection increases the number of crashes at the location (Strauss et al., 2013), while another (Tasic et al., 2017) found that crashes within an area decrease as the number of bus stops increase. Demographics (e.g., population, age, income, employment) were accounted for in three models, with just one reporting significant effects, namely a “negative relationship between the number of crashes and the average income” (Prato et al., 2015, p. 10).

Modeling Approaches

Detecting a SIN effect requires a statistical model relating the number of crashes to exposure and other theoretically relevant explanatory variables. Two models, in particular, emerged as the prevalent techniques in the literature: negative binomial and Poisson generalized linear models. Generalized linear models are similar to standard normal regressions except they allow error terms to be non-normally distributed and may involve transforming the data (taking the natural logarithm). Count data are often modeled using the negative binomial and Poisson distributions. Of the 20 studies with valid real-world models, 12 employed the negative binomial form while 8 employed the Poisson.

Two studies commented on the benefit of the negative binomial model over others: zero-inflated models assume “that there is a zero probability of an accident occurring [at some sites, which] may be an inaccurate assumption, since no traffic site is safe” (Kröyer, 2015, p. 40). Turner et al. (2006) justified the use of the negative binomial model over the Poisson by correctly stating that “the Poisson model is used where the variance in accident numbers is roughly equal to or less than the mean” (p. 68) and that “generally the variability is higher than the mean” (p. 68).

Notably, the research team led by Prato and Kaplan produced the only papers reviewed that made use of interaction terms. In statistical modeling, interaction terms allow for factors to exert different effects on the dependent variable *depending on the values of other factors*. Here, land use is partially crossed with several built environment variables. Specifically, bicycle lanes and paths exert different and statistically significant impacts when in suburban areas, as do roundabouts and traffic lights. The team found that “when considering the interaction with the location in urban or suburban areas, it emerges that bicycle paths are less effective in suburban



areas” (Prato et al., 2015, p. 10) and that “segregated bicycle paths give advantages in terms of a decrease in the number of crashes in general, and even more markedly of severe and fatal ones in particular [with] more pronounced [effects] in suburban areas” (Kaplan & Prato, 2015, p. 9).

Interaction terms are important to consider in statistical modeling because they reduce the potential for omitted variable bias. Re-analyzing the data in many of the studies included in this literature review has potential to improve the understanding of the SIN mechanism, but it can be difficult to obtain the data and such analysis is beyond the scope of this literature review.

Other Methodological Issues

Spatial autocorrelation refers to the tendency of a variable to be correlated to itself in space. This concept may be partially responsible for patterns in crashes between motorists and bicyclists and pedestrians. Four studies addressed this possibility. Osama and Sayed (2016) used full Bayesian techniques to find spatial autocorrelation, while Tasic et al. (2017) found that “stronger spatial dependence exists among total crashes than among severe crashes, for all crash types” (p. 44) by use of generalized additive models. Kaplan and Prato (2015) found that “injury categories show a very strong spatial correlation... suggest[ing] that severe and light injury crashes correlate positively, even after controlling for exposure and infrastructure characteristics” (p. 11). Prato et al. (2015) also found indications “that spatial correlation effects play a significant role in these crash data” (p. 10). Spatial autocorrelation could be acting as a proxy for other unmeasured variables; on the other hand, it could be the result of the same road users traversing segments and/or intersections in close proximity to one another. Regardless, spatial autocorrelation (SA) has been shown to be present in crash patterns and should thus be included in crash prediction models. Failure to account for SA could introduce *omitted variable bias*, potentially causing the misattribution of safety effects to exposure metrics and other variables.

SIN implies a specific order of events: the number of bicyclists and/or pedestrians increases, resulting in a subsequent decrease in the per-user risk of crash or injury. It is possible, however, that these events transpire in the reverse order. Cross-sectional studies can only show that these two events are associated with one another, but temporal analyses can shed some light on this point. Several studies (Tin et al., 2011; Yao & Loo, 2016; Meade et al., 2017) explored and quantified SIN in several time periods but did not address the temporal direction of the effect. de Geus et al. (2012) used a prospective design with participants reporting their bicycling activity and related injuries over more than a year. This design would allow for a temporal analysis of the relationship between bicycling and crashes, but no such analysis was reported. Two studies (Marqués & Hernández-Herrador, 2017; Marqués et al., 2014) of Seville, Spain, found evidence supporting SIN over time but the finding was highly confounded by the construction of 164 kilometers (~102 miles) of bicycling lanes segregated from motorized traffic. Descriptive statistics show an increase in the average number of bicyclists at each observation point and a decrease in the crash rate, but no attempt was made to remove the effect of the newly constructed bicycling infrastructure.



Two studies did adequately address the temporal direction issue. Fyhri et al. (2017) exploited “the natural seasonal variation in bicycling frequency” (p. 124) with a panel survey and video data collection. The authors found that, “the sudden increase of cyclists in spring and early summer results in an increase of situations where overlooking and near-misses happen. This situation is then followed by a situation where the other road users [vehicle drivers] get used to the presence of bicyclists, and then learn to expect them on the roads. This again results in fewer conflicts” (Fyhri, 2017, p. 131) This finding was made using self-reported survey data, which Fyhri et al. admit is subject to “road users’ interpretation of different situations” (p. 131), but “the video observation data shows a quite clear pattern of increase of conflicts (but not risk) from spring to summer and a subsequent drop in conflicts and risk later in the season” (p. 131). Aldred et al. (2017) considered changes in bicycle commuters and motor vehicle kilometers in 1991, 2001, and 2011 and found that “not only do local authorities with more bicycling tend to have a lower per-commuter risk, but places where bicycling grew tended to become relatively safer per commuter, and places where bicycling declined tended to become relatively less safe [more fatalities and serious injuries] per commuter” (p. 6). However, due to the limited number of time periods and the 10 years between each, Aldred et al. admit that they “cannot be sure that more bicycling results in reduced risk, rather than reduced risk resulting in more bicycling” (p. 6).

Three geographical scales (micro, macro, and meso) are referenced in the literature. However, these scales were not consistently defined across studies. There is little disagreement in the literature that micro scale analyses focus on intersections or roadway segments. Tasic et al. (2017) refer to a study of census tracts within Chicago as a macroscopic scale and Osama and Sayed (2016) referred to a study of traffic analysis zones in Vancouver as being at the macro level. Elvik and Bjørnskau (2017) define the meso scale as “street networks or urban traffic zones” (p. 275) while Yao and Loo (2016) define the meso scale as focusing on “the differences within a city” (p. 379) or region. Elvik (2015) compared analysis results across geographical scales and found “no consistent tendency for the safety-in-numbers effect to be weaker or stronger at the meso- and macro-levels than at the micro level” (p. 280).



Implications and Considerations

This section builds on what was observed in the literature review findings to characterize the state of the practice research and summarize key issues to be considered by those with an interest in the SIN concept.



Growing Acceptance for Safety in Numbers

While not without skepticism, there is a great deal of consistency in the literature that there is a SIN effect for both bicyclists and pedestrians. This effect differs by mode, and bicyclists see a stronger effect than pedestrians. The range of regression coefficients were found to be fairly consistent across individual studies and range from 0.09 to 0.67 with a mean of 0.431 for bicyclist volumes and from 0.18 to 0.79 with a mean of 0.498 for pedestrian volumes (Elvik & Bjørnskau, 2017). Using the bicyclist example, this means that as the volume of bicyclists double, one could expect related crashes to increase by $2^{0.431}$, or 35%. Although there appears to be an increasing consensus that there is a SIN effect, there is not a common understanding of what is causing the effect. This section discusses current gaps in the understanding of the SIN effect, implications of the research, and considerations one should take when applying these research findings.

The term “safety in numbers” typically generates the image of a group of entities, in this case pedestrians or bicyclists, who are safer because of the size of the group. While this idea is the general premise of the SIN theory, there are two common ways SIN is defined in the literature. Jacobsen’s (2003) foundational work developed statistical models showing the relationship between motor vehicle-related crashes and exposure of vulnerable road users. This method has been largely followed by other researchers. In other cases, literature has been published citing a SIN effect, but foregoing statistical modeling and looking only at the relationship between number of crashes and exposure (e.g., NYCDOT, 2013; City of Boston, 2013; Marqués et al., 2014). In these cases, the authors typically show that while vulnerable road user exposure has increased, the number of motor-vehicle-related crashes has decreased or rose more slowly than exposure and cite the SIN effect to explain this. These two approaches are quite different. The first approach focuses on safety as individual risk and the second focuses on safety for the entire community. What is commonly absent from these latter examples is the inclusion of other explanatory variables. For instance, during the same period:

- How has funding for and the installation of pedestrian- and bicyclist-related infrastructure changed?
- How have policies changed?
- Are there new programs to provide education or encourage non-motorized transportation?
- How has enforcement of pedestrian- and bicyclist-related laws changed?



Without knowing the answers to these questions, it is difficult to equate the reduced crashes to the SIN theory alone. There are several reasons why these topics are not always discussed related to limitations on relevant data.

Data Limitations

The two critical inputs to nearly all literature on the SIN theory are safety data (e.g., number of bicycle-related crashes) and exposure data (e.g., volume of bicyclists). Gaps exist in research pertaining to both critical pieces. Most research into SIN considers only those crashes between a motor vehicle and a vulnerable road user. There are many reasons for this, but the primary reason is the availability of data. Data on motor vehicle crashes are often maintained by transportation agencies and/or law enforcement agencies. Often, these data are populated through law enforcement crash reports, which are rarely generated for minor injuries. For example, a single bicyclist sliding on ice and crashing on a sidewalk is unlikely to be reported to law enforcement. Similarly, crashes between two bicyclists or a bicyclist and a pedestrian are also unlikely to show up in law enforcement databases, thus there are bicyclist and pedestrian crash types that are not well understood. Better inclusion data sources to quantify minor injuries (e.g., hospital data) would enhance SIN research.

Existing research has varied on different approaches to include exposure data. Some studies (Moudon et al., 2011) use simple proxy data, such as neighborhood density, to estimate exposure. Other studies (Raford & Ragland, 2004) used more sophisticated models to develop more detailed estimates of exposure data. Finally, many studies used actual volume data provided by transportation agencies and/or collected by researchers. While actual volume data are typically preferred for this research, the availability of these data are limited and are costly to collect. To minimize the cost of data collection, researchers are often forced to limit their data collection, both temporally and spatially. Discussed extensively by Kröyer (2016), short observation periods of pedestrian and bicyclist flows can introduce bias and result in unreliable models.

The literature tends to show a SIN effect; however, the reason for that effect is not well understood. Researchers have studied various independent variables to explain this effect. In particular, data related to the built environment or policies and behaviors such as helmet use have been difficult for researchers to include. While researchers successfully incorporated variables to describe the presence of bicycle facilities (e.g., bike lanes), more nuanced built environment variables (e.g., sidewalk condition) have largely not been included in past research. Much like the limitations discussed previously on exposure data, these nuanced variables are rarely available in existing databases and are time-consuming to collect. Further, to ensure that the exposure data sample size is large enough for analysis, researchers often collect several years of data. Researchers find it difficult to track changes in the built environment over the same time period, so even if independent variables related to the built environment are included in the research, it is likely that the variable describes a snapshot in time and not necessarily the conditions experienced throughout the entire study period.



Demographic and behavioral information are rarely considered in existing SIN research. Much of the research into the SIN theory has been completed in locations outside of the United States that have unique walking or bicycling cultures. Schepers (2012) discussed this topic, highlighting that even among European countries, his study's sample population (Dutch bicyclists) are more likely to ride to their place of employment and often do so at a young age. Besides cultural differences, there are differences in behaviors and safety when comparing experienced and inexperienced bicyclists (Daley et al., 2007). By encouraging bicycling without proper education or bicyclist-related programs, the new novice bicyclists joining the population may, at least until they gain experience, be less safe than those with more experience. The same line of reasoning cannot be directly applied to pedestrians. However, pedestrian injury and fatality risk has been found to vary by age group (Bhatia & Wier, 2011). Because of this, the estimated SIN effects for pedestrians may also vary with the demographics of the study area.

This literature review identified 5 studies focusing strongly on the behavioral component to the SIN theory, 3 of which were led by Fyhri. As another example, one of the studies that collected a year's worth of travel diaries and questionnaires (de Geus et al., 2012) did not estimate a formal model with the data. Instead the researchers calculated an incidence rate between three regions and showed a trend consistent with the SIN theory. Given that many hypotheses for the SIN effect include behavioral changes, more behavioral research is needed.

Further, while researchers have consistently found SIN effects for crashes between motor vehicles and pedestrians, as well as motor vehicles and bicyclists, research has also found similar effects for considering only motor vehicles (Elvik & Bjørnskau, 2017), single-bicyclist crashes, single-pedestrian incidents (Kröyer, 2016), and heavy vehicles (Daniels et al., 2011). The research is not clear about the cause of SIN effects in these types of crashes because the nature of the behavior change is not known.

Application

This literature review found many studies investigating the SIN effect, but little literature is available on successfully applying this research to transportation planning, policy, or legislation. References to the topic from transportation agencies in the literature were typically brief, broad, or both. A common theme throughout the literature is that because there appears to be a SIN effect, there will be a positive safety benefit from increasing non-motorized traffic. What is assumed, but rarely discussed, is that even with a SIN effect, increasing the volume of non-motorized traffic will likely increase the number of related injuries and fatalities. Different demographics of road users should be taken into consideration before the SIN effect alone is used to justify encouraging new non-motorized transportation, because different road users will be affected differently. Further, some researchers have used hospital data to look into the number and cause of bicyclist injuries (Kröyer, 2016; Turner et al., 2006; Jonsson, 2013; Ramsey & Richardson, 2017), and findings from these studies show that the number of unreported pedestrian- and bicyclist-related injuries make up a large percentage of the total number of



injuries. Meuleners et al. (2006) found that a substantial number of bicyclist injuries were related to crashes with fixed objects, citing the need for bicycle-friendly infrastructure to improve safety. Some research has referenced the SIN theory from a public health perspective (Götschi et al., 2016), but because the exact cause of the effect is not known, findings from this research are not granular enough to provide much support in applying the SIN theory nor were they discussed in sufficient detail to be interpreted on a broader scale. More research is needed to better understand the implication of the SIN theory from a public health perspective that includes all members of the society and does not focus only on those vulnerable road users involved in motor vehicle crashes.

From a public health perspective, the current SIN research emphasizes the need to consider possible factors underlying changes in walking and bicycling activity. Given that there are still increases in bicyclist and pedestrian injuries as volumes increase, practitioners and advocates should consider adopting a multi-prong approach. The approach should include additional education to inform and support new and vulnerable road users who might adopt bicycling or walking as a mode of transit as well as education for road users about applicable laws and practices (e.g., helmet use). These should also be paired with improvements to the built environment to better support pedestrian and bicycling infrastructure and safeguard these more vulnerable users' safety.

Given the nature of the improvements to the transportation and community infrastructure needed (e.g., pedestrian oriented community design, road diets, posted speed limit, sidewalk condition, bicycle lanes), partnerships between transportation, planning, and health agencies would be important in effectively implanting this kind of multi-prong campaign to increase walking and ridership. Data collected through these partnership efforts could support research to expand our understanding of other variables and factors that contribute to the SIN effect given the multidisciplinary nature of the partners involved. Further, it is important to recognize that other factors such as infrastructure changes or regulation compliance (e.g., helmet use) may have an impact on walking and biking.

In addition, new community health needs assessment requirements (Lopez et al., 2021) that many hospitals have to abide by to maintain their nonprofit status to incentivize their increased collaboration and coordination with community partners, in particular local health departments. This could represent an interesting opportunity to bring health and transportation data together to better understand the nature and extent of the unreported injuries caused by increased bicycling and pedestrian exposure. Once understood, partners could work together to better address those issues through a mix of improved infrastructure, planning, advocacy, and education.



Programs and Initiatives

This section provides an introduction to the state of the practice, providing a sample of bicycle and pedestrian programs in different communities around the Nation. Their objectives and metrics for success are discussed in the context of the SIN concept. Throughout the country there are countless transportation and advocacy organizations that work to increase pedestrian and bicycle travel and safety. Many of these agencies have measures of success – whether that be the implementation of a specific program or initiative, seeing increases in bicycle and pedestrian volumes, and/or the decrease in bicycle and pedestrian crashes/crash rates. However, oftentimes these efforts are not formal evaluations, their results are not formally published, or they do not make the correlation between an increase in pedestrian and bicycle volume and the factors that may influence SIN. This section documents some of the publicly available documentation of program successes and findings related to SIN.



Street Smart Washington, a program in Washington Township in Warren County, New Jersey, provided a report on a 2015 safety campaign. The campaign was initiated to combat the high number of pedestrian crashes and contained the following goals.

1. Change pedestrian and motorist behaviors to reduce the incidence of pedestrian injuries and fatalities in New Jersey.
2. Educate motorists and pedestrians both about their roles and responsibilities for safely sharing the road.
3. Increase enforcement of pedestrian safety laws and roadway users' awareness of that effort.

Campaign activities included enforcement, use of radar-equipped speed feedback signs, community events, and distribution of education and outreach material. Campaign effectiveness was measured through pre- and post-campaign surveys and field observations and found that its goals were met and a reduction in non-compliant observed behavior by drivers and pedestrians was observed (TransOptions, n.d.).

Another Street Smart campaign for the Washington, DC, metropolitan area was aimed at “promoting awareness of the consequences of motor vehicle, pedestrian and bicycle crashes, drawing attention to law enforcement efforts that target behaviors by pedestrians, cyclists and motorists, and recommending ways to reduce risks.” The 2011 annual report documented campaign effectiveness, measured through pre- and post-campaign surveys and collection of videos to document road user behavior. The surveys found that respondents saw non-compliant behavior as being more dangerous after the campaign and increased awareness of risky behaviors, among others and the video footage collected of driver behavior showed reduced non-compliant driving behavior (Street Smart, 2011). While programs such as these affect SIN by encouraging biking and walking, they often do not conduct research or crash analyses to develop literature and mathematically support the SIN theory.



Other agencies or programs have directly tried to quantify the safety impact to bicyclists and pedestrians. For example, in 2013 New York City published a sustainable streets report documenting the NYCDOT's progress towards enhancing safety and mobility in the city. The report alludes to the impact of SIN and it attributes the phenomenon to pedestrians and bicyclists becoming a predictable part of the traffic pattern where biking and walking is high. The study suggests that the introduction of CitiBike, a bike share program, may have accelerated the effect in New York City (NYCDOT, 2013).

In its 2016 Vision Zero Report, New York City also indicated that increasing the number of bicyclists was the best way to improve safety and the way they have encouraged more bicycling is through an increase in the length of on- and off-street bicycle facilities (NYCDOT, 2016). Similar sentiments were noted in the NYCDOT 2017 Safer Bicycling report. The report attributed the growing number of bicyclists as a likely contributor to reduced bicycling fatalities and injuries. While NYCDOT's report alludes to a stronger SIN effect, the city has been focused on expanding and improving its infrastructure for bicyclists. From 2006 to 2016 New York City increased efforts to expand bicycling by introducing bike share, increasing bicycle infrastructure, conducting bicycle helmet and bell giveaways, providing increased bike parking, and hosting bicycle safety training for children. The associated action plan includes continued efforts to expand bicycling facilities along with additional outreach and passing legislation that protects bicyclists (NYCDOT, 2017).

Seattle conducted a citywide bicycle and pedestrian data analysis in 2016. The report analyzed available data on pedestrian and bicyclist crashes and found that the collision rate has fallen over the past decade despite the level of active transportation increasing. The report attributed this finding to the SIN phenomenon and pointed to increased driver awareness where walking and biking rates are an important factor in the crash rate reduction (Seattle Department of Transportation, 2016).

Vancouver and Toronto both published reports similar to Seattle's. The Toronto Public Health Department published a 2012 report on improving walking and bicycling. The report summarized health benefits and risks of active transportation in Toronto and presented suburban and urban crash data for Toronto that supports SIN theory. The data showed that higher pedestrian crash rates were located in areas of lower pedestrian volumes, and lower pedestrian crash rates were found in areas of higher pedestrian volumes (Toronto Public Health, 2012). A 2015 bicycling safety study from Vancouver, found that bicycle crash rates have remained level despite increases in ridership (Urban Systems, 2015). The study also cites SIN as the reason for these findings and identified additional contributing factors such as:

- Drivers are more accustomed to checking for bicyclists on the road;
- In areas where bicycling rates are high, drivers also use bicycling to travel; and
- Areas with more bicycle users likely have more bicycling facilities and safer design.

With improved datasets and increased interest and attention on walking and biking, more agencies are working to understand the factors that impact pedestrian and bicyclist safety.



Following a spike in bicyclist fatalities, Boston published a 2013 Bicyclist Safety Report that recommends programs and initiatives to increase bicycling, improve bicycle infrastructure, enhance education and enforcement, and improve data collection and monitoring so they can better assess the impacts of these investments (City of Boston, 2013). In 2010 the Safe Transportation Education and Research Center (SafeTREC) at the University of California analyzed data from the State and identified two immediate needs.

- The creation of a statewide pedestrian database.
- Additional research on SIN.

The authors cautioned that the SIN phenomenon “undermines the usefulness of pedestrian collision rates as a proxy for pedestrian risk” and recommends further study to understand SIN and factors driving it (Greene-Roesel et al., 2010).

Conclusions



Many transportation and safety professionals are trying to understand what factors influence bicyclist and pedestrian crash risk and how to better improve non-motorized transportation safety. This literature review provided a comprehensive review of SIN, the idea that individual risk decreases as the number of bicyclists and pedestrians increases. This report synthesized the state of the research to provide a clearer understanding of evidence regarding the SIN concept and the factors which should be considered when implementing and evaluating policies or programs that promote walking and bicycling.

The literature included in this report represented multidisciplinary fields of study or areas of practice in order to obtain the broadest understanding of the SIN concept possible. It is important to note that there are many studies of roadway user safety that are relevant to the SIN concept; however, not all authors explicitly used the term “safety in numbers” to define their work objectives or outcomes.

Several conclusions and lessons learned can be drawn from this literature review, which are summarized here.

- There has been research both supporting and critically reviewing the SIN concept, and the increasing agreement in the research is that the effect exists. The majority of the available literature affirms that there is a SIN effect for both bicyclists and pedestrians, supported by a non-linear relationship between pedestrian and bicycle exposure and crash risk. The effect differs by mode, and bicyclists appear to have a stronger effect than pedestrians.



- A statistical/methodological review highlighted methodological issues in several SIN-related studies. A weakness of many SIN-related studies is the data commonly used by researchers. The two required data sources to conduct a SIN-related study are those sources describing exposure and safety, and there have been limitations with both types throughout the literature. Count or volume data are rarely readily available, and collecting this data is often resource intensive. Issues with safety data stem from underreporting of injury data in crash datasets developed through police crash reports. Some researchers have been successful in introducing variables describing the built environment and behavioral characteristics, but these topics are a current gap in SIN research and are often covered only briefly, if at all, by current research.
- It is important to realize that crashes, injuries, and fatalities will continue to increase as more road users are entering the system; the SIN theory states that this increase will be at a rate less than the rate of increase in road users. This also assumes that all other elements of the roadway environment remain stable; other factors may change such as engineering countermeasures or bicycle helmet laws. Changes to these factors may affect walking and biking and safety outcomes. Given that there are still increases in the number of bicyclist and pedestrian injuries as volumes increase, programs to increase pedestrian and bicycling as a mode of travel for individual or community health should consider other factors underlying SIN that may impact activity such as the build environment and road user behavior changes and characteristics.
- Some transportation and advocacy organizations work to increase pedestrian and bicycle travel and safety. Many of these agencies have measures of success—whether that be the implementation of a specific program or initiative, seeing increases in bicycle and pedestrian volumes, and/or the decrease in bicyclist and pedestrian crashes/crash rates. However, program evaluation results are often not formally published, do not make the correlation between an increase in pedestrian and bicycle volume and reduced crashes, or discuss the other factors that may influence SIN.
- The SIN concept is more commonly referred to and used in academia than in practice. More guidance on SIN's underlying factors (e.g., the build environment, behavioral changes, road user demographics and characteristics, safety culture) is needed to help transportation practitioners who want to integrate this theory into their planning and policy.

While this literature review found some consensus in aspects related to SIN, the exact cause of the SIN effect is unknown. Some research points to behavioral changes, others question the involvement of related infrastructure. As work is advanced in SIN it will be important to convey considerations to researchers and practitioners seeking to use SIN to develop policies and initiatives.



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